Master Thesis

submitted within the UNIGIS MSc. programme
at the Department of Geoinformatics - Z_GIS
University of Salzburg, Austria

under the provisions of UNIGIS India framework

Estimation of built-up density in urban area using object-based image analysis (OBIA) for the study sites in New Delhi City (India) and Shenzhen City (China)

by

Syed Murtaza
GIS_104157

A thesis report submitted in partial fulfilment of the requirements of the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GIS)

Advisor (s):

Dr. Shahnawaz

Quetta, 05.01.2019

Science Pledge

By my signature below, I certify that my thesis report is entirely the result of my own work. I have cited all sources of information and data I have used in my thesis report and indicated their origin.

Queta, 05.01.2019

Place and Date	Signature

Acknowledgements

I would first like to thank my project advisor Prof. Shahnawaz of the UNIGIS at University of Salzburg. He was always available whenever I ran into a trouble spot or had a question about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right the direction whenever he thought I needed it.

I would also like to thank the experts who were involved in the providing technical help for this research project especially Juraj Murcko who has provided great support and helpful materials and without his passionate participation and input, the research could not have been successfully conducted.

I would also like to acknowledge my colleagues as the second reader of this report, and I am gratefully indebted to their valuable comments on this report.

Finally, I must express my very profound gratitude to my parents and to my wife for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this report. This accomplishment would not have been possible without them.

Thank you.

Sayed Murtaza

Abstract

Remoted sensing data and other satellite imagery are important sources of information for studying urban environment. Remote sensing data are becoming more widespread as various techniques for processing these remotely sensed spatial data derived from satellite imagery are available. We can obtain the information about land, such as land use, land cover or various land statistics and indicators by the analysis and classification of satellite imagery. One of those indicator is built-up density on defined area unit which represents a portion of built-up area or pre-defined area segment such as administrative district or individual parcels. The spatial distribution of the built-up area may vary greatly within these pre-defined area segments. This master thesis aims to define a method which creates these pre-defined area segments based on the very high resolution (VHR) satellite image data. The method creates boundaries, in which the change in spatial distribution of buildings and other built-up structures is apparent and can be distinguished among several other built-up density classes. The method is based on the concept of object-based image processing approach which is implemented as rule set in eCognition software. The rule set includes image segmentation, land cover classification, built-up area extraction and finally the image object´s shape refinement by using image processing algorithms provided by the software package. The method is explained in the methodology section and it is tested on a very high-resolution satellite image from an urban environment in order to assess the transferability to other image scenes. The land cover classification results are presented and discussed at first and then built-up density classification on a two hierarchical image object levels are performed. The final results are compared and discussed and then the conclusions are made. The improvements and the recommendations for further possible future research are given.

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Terminology

There are several terms and terminology are being used in this thesis. To avoid confusion these terminologies are explained in the beginning part of the document. Some other technical terms and abbreviations are also explained here:

VHR imagery: The satellite imagery having very high spatial resolution and the pixel size greater than 5 m. In this study the images with pixel size of 0.5m is used.

LULC: land use / land cover

Built-up density: The portion of built-up area on the overall area segment or unit under consideration.

Urban fabric: The physical form of towns and cities with elements such as building types, sizes and shapes, open spaces, roads and streets and the overall composition.

Urban typology: The set of spatial and morphological features such as size, shape, spatial distribution and spacing between buildings that are homogeneous in characteristic and exist on one land use type

Area segment: The area surrounded by certain defined boundaries such parcels, administrative boundaries, road network.

Extended/broader built-up area segment: The overall envelope of the built-up area with compact and continuous segment which includes associate land between and around building and excludes large not-built-up open spaces.

Chapter-1

1. Introduction

1.1. Background

The urban feature extraction from high resolution satellite (HRS) imagery, as stated by **Erener (2013)** is an essential remote sensing method that has numerous applications in urban planning and mapping, calamity administration, updating the geographical information systems and so forth. The publication likewise expresses that using the remote sensing techniques and methods helps in gathering vast scale information with no physical contact. Physical structures in an urban area are the most vital highlighted standout features, whose complexity has urged the development of new algorithms for as far back as three decades.

Today in our modern society maps and other types of spatial data are being increasingly used in daily life. The rapid rate of urban expansion is mainly due to the population growth together with the improved efficiency of transportation and the increased number of cars. This expansion in the urban population has created many problems that include climate change, depletion of energy resources, water scarcity, pollution, loss of wildlife or loss of agricultural land amongst others **(De Paul & Vincent, 2007)**.

According to **UN-Habitat (2016)** more than 50% of the World population live in cities today. The world urban population has reached to 7.7 billion, almost one third of this population lives in unhealthy, polluted areas with an inadequate sanitations and uncleaned drinking water. It is estimated that by the year 2020, Asia will have the highest number of urban inhabitants, followed by Latin America. Lagos in Nigeria in Sub-Saharan are expected to be among the largest cities in the World.

Normally information about the urban planning, analyzing and other urban problems such as urban extension are acquired using aerial photogrammetry. However, with the advances in space technology, satellite remote sensing has increasingly found most useful in the analysis and planning of urban environment. The current sensors technology is producing and delivering data with high potential for use in scientific and technological researches. The results from these researches reflect the current state of urban land use, infrastructure and natural resources. These results could also contribute to sustainable urban planning **(De Paul & Vincent, 2007).**

Most of the authors describe that the high-resolution imagery like satellite imagery or aerial images help recognition of urban features however it turns into a troublesome assignment because of their high unearthly and spatial inconstancy.

As indicated by **Erener (2013)**, there are numerous variables that influence object identification from high resolution satellite imagery in an urban object. He likewise said four variables affecting the recognition of urban structures, which are surface material (e.g. soil, block, metal, and so on.), dynamic items (e.g. autos, markets or squares, and so on.), obstruction due to shadow or contiguous features lastly sensor or climatic elements. These components make it a difficult task to build up a generic solution which can extract features from various sorts of imagery.

Aytekin (2012) in his research specified that prerequisite of exceedingly skilled work, manual effort, cost and time engaged with manual digitization of urban objects have motivated the researchers to mechanize features extraction methods which will build the speed and reduce all the resources required.

There are numerous classifiers for feature extraction like Support Vector Machines (SVM), Maximum Likelihood Classifiers (MLC), Neural Networks Classifiers (NNC), Decision Trees Classifiers (DTC) and Object Based Image Classification **(Blaschke T. , 2010)**

Object Based Image Analysis (OBIA) is analyzing group of pixels as they are usable objects that can relate image processing techniques and GIS functionalities to tackle real-world issues **(Hofmann P., 2004)**.

Blaschke T. (2010) mentioned that OBIA is an integration of numerous remote sensing image analysis methods like division, edge detection and feature extraction, He further adds on page 3, that, "OBIA has bridged any barrier between spatial ideas of multiscale landscape analysis, Geographic Information System, Geographic Information Science, and the collaboration between image objects and their radiometric attributes and analyses in Earth Observation Data." Further **Aytekin (2012)** mentioned that utilizing rule based and substance driven methodologies classification of substance like vegetation, structures, streets, and so forth., is conceivable.

The poverty level in urban area can also accelerate environmental degradation. Land use and land cover (LULC) changes can result in the transformation of the habitat which results in the microclimatic pattern degradation **(De Paul & Vincent, 2007)**.

Of every single urban component, classification of vegetation can be effortlessly performed by utilizing NDVI **(Aytekin O., 2012)**, however to outline urban structures and streets in such a simple way would be troublesome at because of factors specified **(Erener A., 2013)**. To overcome such issues and separate urban structures from other objects either thematic data or elevation data were utilized for building detection **(Awrangjeb M., 2010)** and **(Hermosilla, 2011)**.

The issue with thematic extraction is that it requires numerous resources specified before while the accessibility and cost engaged with elevation data of high resolution to suit urban structures such as building detection is imperfect. In both the cases, high resolution imagery is ordinarily required, so this research aims to develop a novel way to deal with diminish manual exertion, time and cost associated with these strategies. From the above passage, urban feature extraction turns into a complex issue and to address these issues of visual translation techniques might be the best. **Haralick et al. (1973)** describes that image are pictorial data spoke to as an element of two factors, and specifies that an important method to depict this pictorial data is to search for human methods for interpreting this data.

Awrangjeb et al. (2010) and **Hermosilla et al. (2011)** likewise say that human interpreting of color photos includes three major fundamental components which and these are spectral, textural and contextual components. Spectral data are the tonal variety of an object between various groups of electromagnetic spectrums, though textural data are the spatial distribution of tonal variety inside a band and relevant data is the connection between the block of pictorial information that is being analyzed, **Kundu & Pal (1986)** on page 433, express that, "visual data is gathered at purposes of large spatial variety of light intensity in an image".

From this information on visual understanding, the properties required to depict an object in OBIA can be resolved into two sorts which are common describers and visual describers. Here, band ratios are being considered as regular describers, as utilization of vegetation lists for biomass estimation limited the impact of soil background, time of capture and sensor view angle, as said by **Nichol and Sarker (2011)**, While, edge detection and textural properties are being considered for visual describers as they help in getting visual data.

In a study **Anderson et al. (1976)** introduced a scheme of classification with four categorization level of urban materials. In the first categorical level four categories such as built-up objects, vegetation, water bodies and non-urban bare surfaces are presented. The second level further distinguishes objects between their functional use like buildings, transportation areas, sport infrastructure etc. In the next level of categorization, the objects already categorized are further classified according to their building material. This scheme is very comprehensive and one can be encountered with a vast amount of different types of objects in an urban environment. This approach needs the design and implementation of automatic analysis of the satellite image data and the extraction of desired information.

The urban landscape is different from other natural landscapes due to its high proportion of artificial man-made objects and high variability of surface materials. These combinations of artificial man-made surface are called built-up areas. The urban built-up areas can be defined as region which contain structural information about the urban domain, such as buildings and open spaces, roads and parking lots. These structural areas are often referred to as impervious surfaces. What defines urban landscape and makes it different from other natural landscapes is high proportion of artificial man-made objects and high variability of surface materials. We call these conglomerates of artificial impervious surfaces built-up areas **(Limin Yang, 2003).**

The imbalances between geography, ecology, economy, society, and institutions are making the “emerging futures” of many cities doubtful. The expansion of economic activities and the environmental changes caused rapid demographic and spatial growth in cities which have made the local and governmental institution unable to manage effectively. The unplanned and unmanaged, urbanization can lead to increase in the growth of slums and disastrous impacts on climate change **(UN-Habitat, 2016).** To make sure that urban development in the cities are secure, sustainable and well planned, it is important to monitor and map the development activities and planning. The new and emerging technologies with the help of satellite images and other remote sensing data give patterns of urban growth and record data using Geographic Information System (GIS) which provide tools for analysis and visualization for transforming the data into information which can support urban planners and local authorities in decision-making.

We can get up-to-date and area-wide information about the extent and structure of an urban area using remote sensing. We can extract land cover and land use (LULC) information from high resolution satellite imagery and which can serve for the city managers and planners to make well-informed decisions about further development in the urban area. The major applications of remote sensing technology for urban environment include urban extension monitoring, urban vegetation management, energy and infrastructure management, transportation planning, security, natural hazards modeling and management or various academic research projects.

In remote sensing systems the urban landscape is a very complex environment because it consists of different types of materials on a very small area. The landscape includes residential, commercial, industrial buildings of different size, shape and material. Various kinds of bare and mixed surfaces such roads and parking lots, trees, parks, gardens, cemeteries, water surfaces.

1.1.1. What is Built-up Density

Built-up density can also be related to population density. We can calculate population estimates for various area unites such as administrative districts, city zones or individual parcels using built-up density if land cover data are available for the whole area. It can also be calculated on regular square grids of the specified cell size.

Built-up density is an index of urban growth and its quantitative information is used as useful tool for urban applications such as urban study, land use changes, illegal building development, urban expansion. Built-up density is the proportion of built-up surface on the total surface on an urban area **(Iossifidis C.H., 2000)**.

The main disadvantages of all these calculation approaches are, that these area units do not represent the actual distribution of built-up area. The outlines of the built-up area normally do not follow the boundaries of pre-designed area units. If there are open spaces or different types of urban typology within the same area unit, the resulting calculated built-up density is not the actual representative because it gives only one number for the whole area unit ignoring the difference in urban typology inside that area. This study aims to develop an approach that would separate these different built-up areas into individual area units having similar urban typology and uniform spatial distribution.

1.1.2. Object-based Image Analysis (OBIA)

Object-based image analysis (OBIA) techniques were developed because of the availability of increasing spatial resolution and very high spatial resolution (VHR) imagery. The individual pixels are not analyzed, but rather groups of pixels which are referred to as image objects. The image segmentation generates image objects. Image segmentation is an important step in the object-based image analysis, Image segmentation techniques enhance automatic classifications using not only the spectral features, but also object shape, texture, hierarchical and contextual information **(Hofmann P., 2004).**

The object-based image analysis is done by segmenting the image into regions with similar spectral values called image objects. The purpose is to get image objects that best represent real world objects. Different features of spectral, spatial or textural parameters of the image objects such as mean reflectance value, area, perimeter, roundness and many others are calculated which can then be used in the classification process. The main purpose of finding optimal parameter optimal parameters of segmentation is to avoid over-segmentation or under-segmentation and thus finding meaningful optimal objects which match real world structures **(Holt A., 2010)**. The optimal results can be achieved by defining segmentation parameters, such as scale and others can be usually defined by the user.

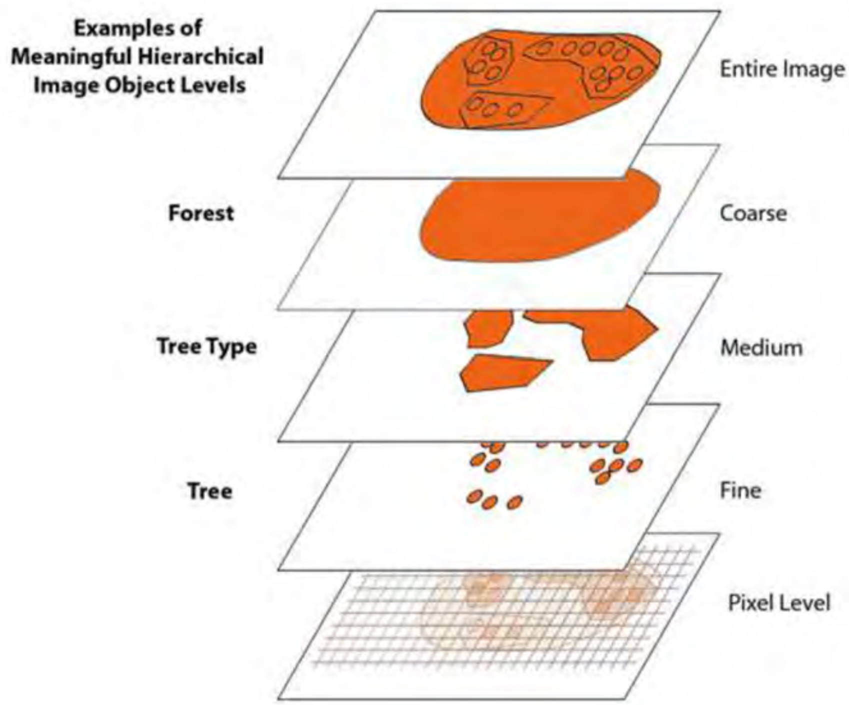


Figure 1 The hierarchy of image objects (Source: eCognition User Guide (2018))

Benz et al. (2004) state that an object is a gathering of pixels called segment, this aides in making important data to relate object with real-world objects. These relations are created by estimating textural, shape and topological data of an object.

Wuest and Zhang (2009) express that the improvements in spatial resolutions of satellite images have limited the pixel based methodology as the separation between the objects have expanded. This inspires the objects oriented paradigm. The expanding disappointment in pixel based image analysis has lead **Blaschke & Strobl (2001)** to bring up the issue "What's wrong with pixels?". They additionally expresses that a large portion of the work related to OBIA revolved around the software product "eCognition".

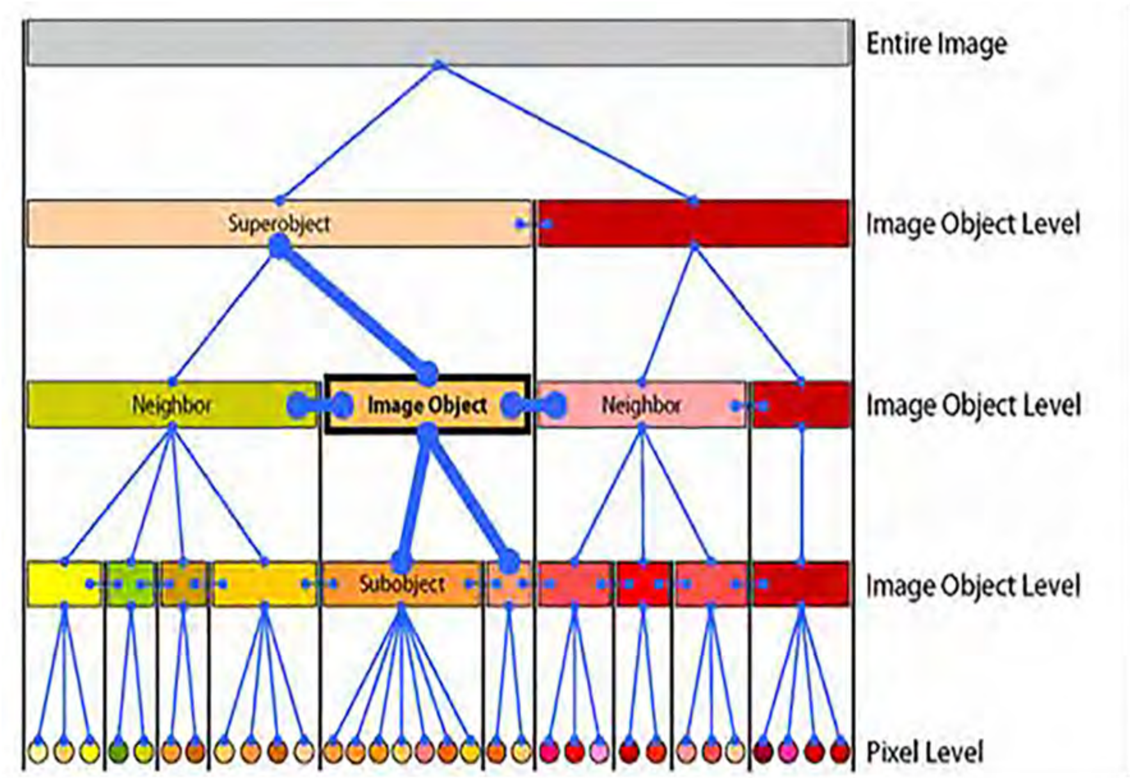


Figure 2 Image object hierarchy and relationships (Source: eCognition User Guide (2018))

OBIA approach can analyze an image at different hierarchical levels. Segmentation process creates image object in hierarchical levels. Firstly, segmentation algorithm is applied to the pixel level to create the first an image object level, or to an existing image object level to refine it and to create new sub-levels or super-levels. At this level different image object levels are aware of each other and know their hierarchical relationships. Every Image object has its neighboring image objects at the same hierarchical level and the sub-objects at the lower level and multiple image objects are part of a super-object in a higher hierarchical level. These hierarchical relationships among objects can be used to describe class properties.

Aerial or satellite image may be first segmented into parcel level using a vector thematic layer of existing parcels and then further on into analysis level to identify buildings, water bodies or vegetation. The user can perform analysis on the analysis level to make use of various image object relationships and then to calculate overall statistics and indicators for the super level which is the parcel level in our case.

The pixel-based classification approaches normally do not consider contextual information of image objects which are sometimes required to interpret the satellite imagery (De Jong, 2003). The internal spectral variability of each land-cover class increases at the same time the spectral variability between different decreases **(Bruzzone L. & Carlin L., 2006)**.

OBIA is mostly applied to very high-resolution images the resulting image objects are normally composed of many pixels with similar values. This approach is very useful, especially when analyzing imagery of very high resolution such as an urban environment, where the variability of spectral reflectance values of pixels is very high. The pixel-based image classification approach results into "salt and pepper" effect in case of high resolution images. The remotely sensed imagery with high resolution has reduced the problem of mixed pixels that are present in low or medium resolution images such as AVHRR, MODIS or Landsat, where more than one class is contained within a single pixel **(Herold M. & Scepan, 2002).** The accuracy of the result of the land use classification very high resolution (VHR) images using pixel-based approach may decrease because of the increase within the class variability of the high-resolution data. Object-based image analysis approaches use spatial autocorrelation in the classification process to in order check the probability of class membership. Based on the above facts and properties, object-based image analysis approaches have become more suitable due to their increased functionality for classification of very high-resolution imagery **(Blaschke T. L. S., 2000)**.

1.1.3. Image Segmentation

The image segmentation goal is to produce image objects with defined boundaries having uniform shapes and unique textures that represent real-world objects. Several image segmentation algorithms and object based image analysis software packages available, the selection depends on the application.

Image segmentation is the first and most important step in object based image analysis. Image segmentation algorithms merge homogenous pixels into image elements and enable the differentiation between heterogeneous neighboring regions **(Schiewe J., 2002)**. On the off chance that the littlest development surpasses the edge characterized by the scale parameter, the procedure stops. Multiresolution segmentation is in this manner a nearby enhancement system and is controlled by the scale parameter. The subsequent sections (image objects) of this question based methodology come nearer to the spatial, pixel value and textural qualities of this present reality structure. The scale parameter likewise decides the most extreme permitted spectral heterogeneity of neighboring pixel esteems inside the subsequent image objects **(Wurm M., 2010)**.

Multiresolution segmentation algorithm is a bottom-up area developing technique, beginning at the pixel level and combining pixels into image objects. In ensuing advances, small image objects with comparative spectral qualities are converted into larger objects **(Hofmann P., 2004)**.

1.1.4. Image Classification

The most commonly used methods to extract land cover and other remotely sensed data is called image classification. The pixel based classification techniques take into account the spectral reflectance values of individual pixels of the images and then classify them into classes having define spectral values. There are many classification techniques to extract meaningful information from imagery. There are many classification techniques developed over past few decades. These techniques aim to classify homogenous features in the image being studied in similar classes. These classes can be defined prior classification known as supervised classification or automatically defined by software application using a clustering algorithm also known as unsupervised classification. Remote sensed images consist of pixels which are organized in rows and columns, so conventional land cover mapping is done per pixel basis **(Smith & Dean A.M., 2003).** Remote sensing technology has been widely used in land use and land cover (LULC) classification and change detection, but it is very rare that classification accuracy with greater than 80% achieved by pixel-based classification algorithm (also called hard classification) especially in the case of urban land use and land cover area (Mather P. M., 1999)**.** On other hand, fuzzy approach (soft classification) to LULC classification is being applied where each pixel is assigned class membership rather than a single label **(Wang F., 1990).**

1.1.5. Land Use and Landcover (LULC)

Land use and land cover dataset are very important sources for many applications and studies such as urban planning and management, socio-economic studies and environment evaluation. The timely and accurate availability of mapping land use and land cover (LULC) is often needed for such studies. The economic growth and population in urban area has resulted in the expansion in past few decades. Many approaches for remote sensing image classification has been developed in but it is still a challenge because of the complex urban landscape and limitation of in remote sensing data **(Qihao Weng, 2010).**

Land use and land cover are normally used interchangeably in literatures however they represent different things. The term land cover refers to a biophysical state of the earth's surface and sub-surface including soil, topography, surface water, ground water and man-made structure **(Skole D., 1995).** Land use describes the human activities on the land, such as agriculture, forestry, building, infrastructures construction that modify the land surfaces in other term land use is the human employment of land cover type.

1.1.6. OBIA Rule-set and the Transferability

The rule-based classification is a valuable approach because it can be reused fully or with minor change. OBIA as a model has always led spatially and thematically improved classification in analyzing remotely sensed imagery than pixel based approaches. Due to the high complexity of image content, it is still very rare to have a robust and transferable object-based automatic solutions without human interactions. With varying imaging conditions or different satellite sensors and their chrematistics, the variability of object's properties is hardly predictable **(Hofmann, 2015)**. On the other hand, the rule-based approach does not use any sample for the classification, it is based purely on the expert knowledge of the user. The user develops a set of condition or rules, called as rule set for each target class. The image objects feature such as spectral means, value, size, shape, texture or different contextual image feature are used in the rule set development. When the image object fulfills the criteria, it is classified in one class. The advantage of the rule-based approach is that the user has full control of the classification process with the full control what does and what does not belong to the class. The other advantage of this approach is that the rule-set is transferable to another image, so it can be re-used again in another project.

There two main approaches of object-based image classification – supervised and rule-based. Object-based. Supervised classification is the same as pixel-based supervise classification, where classification is based on selection of training samples that are used to train classification algorithm. The only different between pixel and object based approach is that instead of single pixels or random group of pixels compact image objects with calculated features are selected. Supervised object classification algorithms are Nearest Neighbor (NN) classification, Standard Nearest Neighbor, Fuzzy membership function.

The developed OBIA rule sets have potential to be transferred, they often need to be adapted manually or the classification results need to be adjusted in pros-processing steps.

Based on above facts, we can define the transferability to be the degree to which a particular method is capable of providing comparable result for two different images. A rule-set is said to be easily transferable if it requires minimal manual adaptation for different imaging conditions. This study aims to develop and describe a robust and transferable rule set for OBIA classification of two different very high resolution (VHR) urban scenes with different spectral, spatial, and textural properties.

1.2. Research Objective

The main objective of this master thesis is to describe, develop and implement a semiautomated object-based image classification approach. Using this approach, we will map built-up areas and classification of built-up density within blocks that are homogeneous in their urban fabric. These built-up density blocks are not a priori defined, they are created based on the remote sensing image data.

In this approach a very high resolution (VHR) imagery is used and it is assumed that the 4 band (RED, GREEN, BLUE, NIR) VHR image and free OSM vector data of the street network of the same area is available. No additional inputs, such as DSM, LiDAR point clouds, land cover or building footprints are assumed to be available.

1.3. Area of Focus

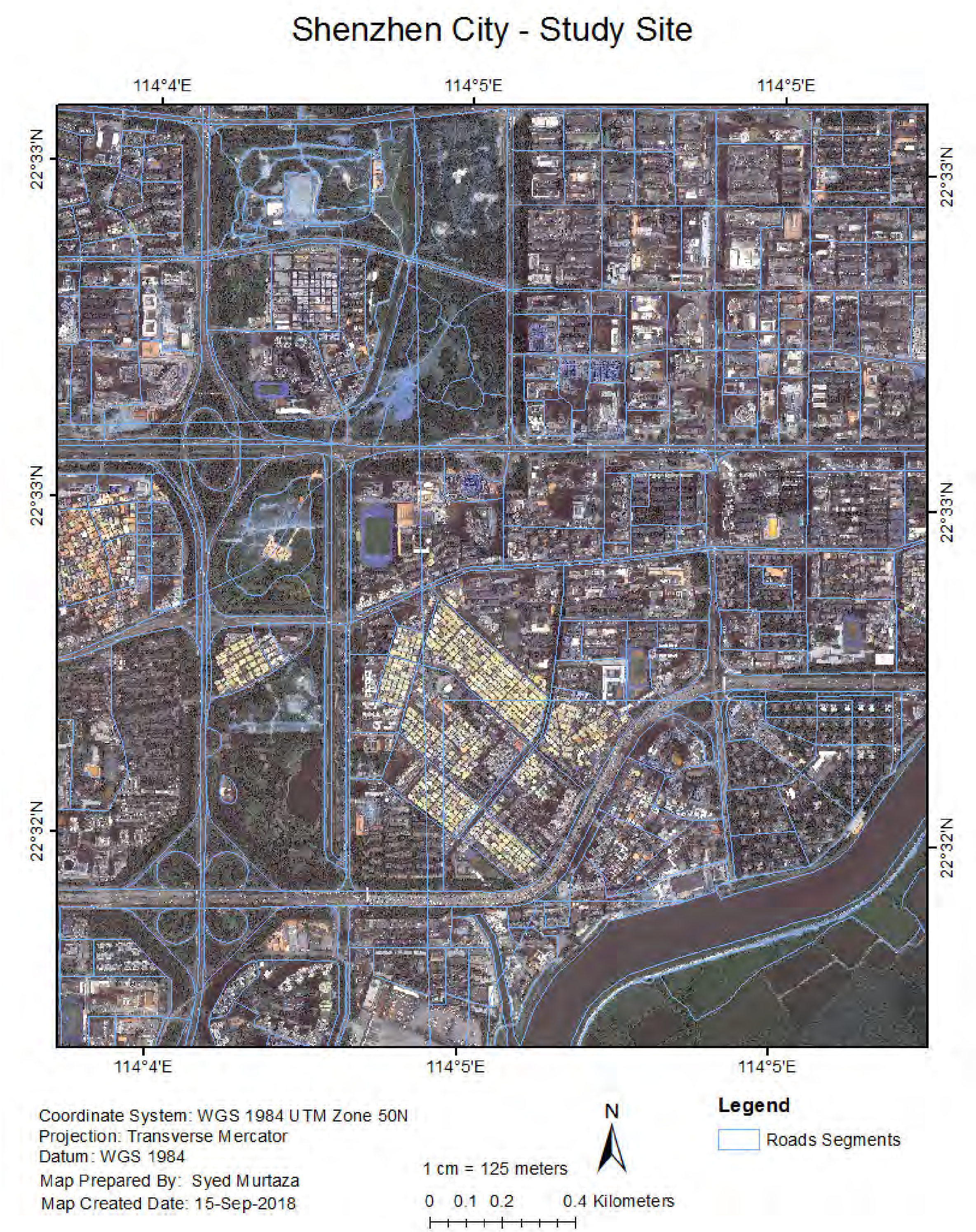
Nowadays spatial data play a very important role in the planning and management of cities; however, the availability of update-to-date data are an issue in many parts of the world which is one of the reasons for poor management and planning in those urban areas.

Most of the population live in the urban areas globally, which increase day by day, so it is important to monitor and study these urban areas. Cities should be developed in a sustainable way so that avoiding the over populated spaces with buildings, degradation of land use and environment. Not only the future cities should be designed and planned, but also the existing cities must be improved in terms of planning and management. This thesis aims to map built-up density across cities using very high resolution (VHR) images and free available road network (OSM) vector layer. The resulting map could be used by local authorities and urban planners. Researchers for studying the urban environment can integrate the result in their GIS workflow. The local authorities and urban planners are always interested in various spatial data such as land use and land cover (LULC) and their changes over time, roads and infrastructure networks and different land statics. However, these data are not always available and must be either purchased from third parties or manually created which requires a lot or resources in terms of manpower, time and financial resources. Researchers have developed various methods to extract spatial data from aerial photogrammetry and satellite images.

1.4. Study Area

1.4.1. Shenzhen City (China)

The study site of Shenzhen is located in the south-western part of the city. In the north of the study area, the land is mostly developed, (in other words) covered by buildings or other built-up structures. There are parts with small (where there are lots of homes) detached houses, as well as big neighborhoods of mid-rise to high-rise apartment panel block houses and their (next to) recreational, commercial and service areas, such as parks and lakes, sport facilities, shopping centers and others. Motorway city ring passes through includes the neighborhood in the north and creates a visible border between built-up and non-built-up land in some places. In the middle part of the scene, a stripe of forest cuts through and visually separates the city from its outer areas and (away from cities) land in the south. There are villages with low-rise detached houses around the scene also. As we can see, there are many different types of (small views of nature scenes) in this scene and bit of water way and channels.



Map 1 Study site in Shenzhen City - WorldView-2 image (Source: satimagingcorp.com)

1.4.2. New Delhi (India)

The examination region of New Delhi under study is a focal part of the city. This study site has been selected to test the transferability of the rule-set. The urban morphology is portrayed by opposite street arrange and a high density of for the most part low-ascent structures in local locations. In the eastern part of the scene, there is a bit of Yamuna River and subordinate waterway channels and lakes. In the close-by local location, there is an impressive measure of urban vegetation. Anyway, in the focal part of the scene, in the downtown area around the railroad station, the building density increments and less vegetation are available. In the focal west piece of the scene there is a major green zone that relates to recreational zone and a college grounds. In the focal west part, more green and recreational space is available, in the east, much higher measure of green zones can be seen, as parks and gardens. We are able to see some urban examples and outwardly survey the built-up density in various parts of the scene.

Map 2 Study site in New Delhi - WorldView-2 image (Source: satimagingcorp.com)

1.5. Literature Review

There are several researches works on the topic of object-based image analysis for the land use and urban area built-up structures. Some of the studies focused on the development of rule-sets for an environment and testing different parameters and image properties to identify objects of interest, some of the studies carried out the transferability of the OBIA knowledge base to another environment. The paragraphs below discuss some of those researches.

In their study of building recognition using aerial images, **Shufelt & McKeown (1993)** give data of some building recognition systems with aerial images. They looked at four urban detection techniques that utilized edges and shadow data for finding structures and separating them from single intensity airborne images. This technique describes a pixel based assessment method for building identification that uses manually digitized urban structures as reference.

In another study the researchers **Lin & Nevatia (1998)** utilized **Shufelt & McKeown's (1993)** evaluation techniques to identify building rooftop created from edge data that relates states of structures in an airborne image to those on the ground and 3-D evidence (Shadow data) to depict a building rooftop.

There have also been some researches on already developed techniques of information extraction. In a study **Seema Jalan (2011)** investigated the performance of object-based image analysis and information extraction from high resolution satellite imagery. The performance of the developed approach was assessed in different urban land cover using CARTOSAT-1 and IRS-P6 LISS-IV images. The results that were obtained that OBIA is fast, simple, flexible and very efficient semi-automatic tool that can manage high spatial and spectral heterogeneous high-resolution image from an urban environment. Image objects having the shape and texture characteristics together with the traditional spectral signature when classified using image based analysis techniques, the resulted map having the high correspondence with real world objects. The parameter defined for segmentation and class descriptions developed for one area were successfully transferred to another area with minor manual adaptation. **Flanders (2003)** expressed that the approach has the flexibility visualization of resulted maps at different level of classification hierarchy and the integration of the classified image products into GIS environment for further spatial analysis. If the class description such as input image data, sensor and imaging conditions do not rely on spectral characteristics of image objects, higher classification accuracies in inter-image transferability may be achieved for image with similar ground conditions.

Sirmacek & Unsalan (2008) utilized color and shadow information two separate structures in view of box fitting methodology, in this they utilized Canny edge detection to help their methodology.

Duan et al. (2004) used thematic information for removing structures from high goals satellite symbolism in which he included fuzzy connectedness relationship for each thematic building and edge information in which centroids of building objects in a topical layer were utilized as seeds.

Müller & Zaum (2005) extracted urban structures from shaded aerial images utilizing a well-ordered methodology. In this, features were extracted that fulfilled certain criteria set on color information, geometric estimations, photometric features and structural features and made a numeric vector in order watching a few examples, this numerical classification was supported by a relevant arrangement which utilized probabilities to settle the yield.

Song et al. (2006) used manually chose building samples and built up a model that utilized surfaces and shapes to show structures that were utilized as prior information. They utilized this prior information to identify Building like Regions (BLR's) and Candidate Building

Regions and utilized CBR as seeds to group regions. At that point they built up a theory to create 2-D housetops, and verified it either by shadow data or by geometry and size.

Tateishi et al. (2010) developed a combination outline work to extract structures, in this optimal feature assurance that included MLC, a framework was utilized to incorporate spectral information, micro-textures scale surfaces and full-scale surfaces.

Cetin et al. (2010) extracted structures from satellite image utilizing the Adaboost algorithm, this tried 137 textural features includes and chose the best performers for building detection.

In another study the researcher **Pankaj et al. (2013)** studied about the transferability of object-based image analysis rule sets for slum identification from very high resolution (VHR) imagery. In the study a set of image-based parameters were identified to differentiate the slum area from non-slum areas. The method was implemented on several different images to test the approach transferability and the results show that textual features, contrasts and the size of image segments is the stable parameters for classification of built-up area and the identification of slum areas.

Aytekin O. et al. (2012) used pan-sharpened high-resolution satellite imagery to extract urban structures by a multi-step process. These steps were intended to eliminate features highlights that are not buildings. At first shadow and vegetation were masked out using a ratio of the hue to intensity and NDVI. At that point the image was smoothened using Mean Shift filter and lastly morphological operations were performed that eliminated out undesirable objects and separated artifacts.

Vivek Dey et al. (2011) likewise utilized a well-ordered end process, here trees were disposed of by NDVI, at that point shadows of numerous types were eliminated, at last roads were eliminated with utilizing Gaussian-Maximum Likelihood function. At that point the distinguished shadows were used as a reference to identify structures in view of shadow object geometry. The neighboring items were recognized as structures by moving the centroids of the shadows toward the path sun azimuth angle. This created an exactness of 72% for a pan-sharpened image and 67% for a resampled multi-spectral image.

The automated detection of urban features is often very challenging because of variations in the spatial and spectral characteristics of the input data. **Hamedianfar and Shafri (2015)**, in their study, investigated the transferability of by utilizing the rule-based structure of OBIA on three different subsets of world view 2 (WV-2) images. The spectral indices, spatial and textural features were incorporated in these rule-sets. The rule-sets developed for one image were tested on two other scenes with accuracies of 88% obtained for all the three images. The OBIA framework provided a transferable process of detecting the urban features without any further manual adjustments. This framework can be applied to other images and study areas or temporal WV-2 image series for the accurate detection of urban area land cover.

In another study **Salehi et al. (2012)** developed a hierarchical rule-based object-based classification framework, in order to classify a complex environment, based on a small subset of QuickBird imagery coupled with a layer of height points. In this rule-set, different contextual, spectral, spatial, morphological, or thematic image features was considered to classify surfaces. The Multiresolution segmentation parameters were used with optimized fuzzy-based Segmentation Parameter optimizer (FbSP optimizer) which was developed by **Zhang et al. (2010)** is an automatic supervised approach to estimate of the three optimal multiresolution segmentation parameters such as scale, shape, and compactness using the spectral and spatial information of training objects utilized in a fuzzy interface system. Once the first level of segmentation completed several sub-objects are selected as training objects. The information such texture, brightness, area of fit is then used as training objects train the FbSP optimizer which gives the optimal parameter for the next level of segmentation after the training. The process can be repeated until the optimal image objects represent real world objects. In this study the classification of urban environment aimed to classify real world object such as trees, grass, shadows, parking lots, streets and buildings in both QuickBird an IKONOS image. The same classification framework and a similar one using slightly different thresholds were applied to larger subsets of QuickBird and IKONOS images in order to assess the general applicability or transferability of the rule-set. The overall accuracy of 92% and 86% with Kappa coefficient of 0.88 and 0.80 were achieved for both the image sets. This study suggests, that the rule-set needs to be developed using a small subset of the large dataset and then can be applied directly to the entire dataset. It also explains the usefulness of ancillary data in combined with object-based image analysis for urban land cover classification of very high resolution (VHR) imagery. The ancillary that was employed proved to be useful for separating parking lots of building and roads called Spot Height data layers.

Walker & Blaschke (2008) in another study carried out by utilizing object-based approach in the development of two urban land cover classification schemes on the true-colour high resolution (0.6 m) aerial photography. The initial developed classification scheme was heavily weighted by standard nearest-neighbor (SNN) functions generated by samples from each of the classes that produced an enhanced accuracy (84%). After that, a second classification procedure was developed from the initial classification scheme where the SNN functions were transformed into a fuzzy rule set. The rule set created a product that is transferable to different subset areas of the image or for land-cover change detection with similar imagery. The comprehensive accuracy assessment shows that the results of the entire rule-based classification are a bit less accurate with an overall value of 79%. This study concluded that the classification scheme with transferability is satisfactory for general land cover analyses, but the classification accuracy may be enhanced at site-specific venues combination of nearest-neighbor functions using class training samples.

Chapter-2

2. Methodology

2.1. Data

2.1.1. VHR images (New Delhi and Shenzhen city)

The semi-automatic extraction of urban features and the classification of built-up density is based on very high spatial resolution (VHR) satellite imagery and object based image analysis (OBIA) software. Two VHR satellite scenes were used – worldview-2 of part of large cities New Delhi and Shenzhen. Since this is a commercial product and the data was provided by company worldview website, that holds all the rights for their distribution. The pre-processing of the image data such as orthorectification, geometric corrections and haze reduction was done by the data provider, using PCI Geomatica software.

General Information	**Band and Wavelength**
Sensor: WorldView-2	**RED** - 450-510 nm
Location: New Delhi (India)	**GREEN** - 510-580 nm
Acquisition: 2010-09-10	**BLUE** - 630-690 nm
Bands: RED, GREEN, BLUE and NIR	**NIR** - 770-895 nm
Panchromatic: 0.5m	
Multispectral: 2m	
Source: www.satimagingcorp.com	

Table 1 New Delhi city study site VHR image data description

The study scene is a WorldView-2 image of Part of New Delhi city. The image was acquired on 10.9.2010 having the spatial resolution is 0,5m (pan-sharpened) which contains 4 spectral bands – R, G, B, NIR. The image was geometrically corrected, orthorectified using RPC method and georeferenced by the provider. The panchromatic band was enhanced and used the spatial resolution to 0,5m. The scene has the projection

WGS_1984_UTM_Zone_42N. In order to make the image to be comparable with the other image. The data format converted to TIFF which was obtained in PCI (.pix) format.

Information	**Band - Wavelength**
Sensor: WorldView-2	**BLUE** - 450-510 nm
Location: Shenzhen (China)	**GREEN** - 510-580 nm
Acquisition: 2012-08-21	**BLUE** - 630-690 nm
Bands: RED, GREEN, BLUE and NIR	**NIR** - 770-895 nm
Panchromatic: 0.5m	
Multispectral: 2m	
Source: www.satimagingcorp.com	

Table 2 Shenzhen city study site VHR image data description

The study scene is a WorldView-2 image of part of Shenzhen city. The image was acquired on 2012-08-21 having the spatial resolution is 0,5m (pan-sharpened) which contains 4 spectral bands – R, G, B, NIR. The panchromatic band was enhanced and used the spatial resolution to 0,5m. The scene has the projection WGS_1984_UTM_Zone_50N. The data format was in TIFF format.

2.1.2. Thematic Data

The additional road network from OpenStreetMap (in shapefile format) was added as a thematic layer in the segmentation process in order to help delineating built-up density analysis segments.

2.2. Pre-processing techniques

Some preprocessing techniques must be applied to make the obtained data used for analysis in this study before the actual image analysis and classification could be conducted. The pre-processing includes atmospheric correction of the image, bit-depth conversion, geo-referencing and co-registration of the images.

2.2.1. Atmospheric Correction

The radiometric correction is an important step in the analysis of remote sensing imagery which removes the effects of atmosphere on the reflectance values of the image. One of the major issues in the visible or near-infrared remote sensing is atmospheric correction because the presence of the atmosphere which always influences the radiation from the ground to the sensor. Quick Atmospheric Correction (QUAC) has been applied to the input VHR imagery to compensate the atmospheric and sensor inherent effects. The radiometric correction transforms the raw digital number (DN) value or radiance value into surface reflectance. QUAC method works with the shortwave infrared such as visible and near-infrared. This correction has been applied the image under study by the provider so that to correct their histogram which is important for the transferability of the developed rule set. **(Harris-Geospatial-Solutions, 2018).**

2.2.2. Clipping Image

In case of WorldView-2 image of Shenzhen, the image was not in a rectangular shape, but in an irregular tilted shape, probably in the original extent taken by satellite. This resulted in the areas on the borders outside of the image data, but within the rectangular bounding box of the image having a value of 0. These pixels were at first assigned NoData value, but this caused that the pixels within the image, which had value of 0 in one of the bands were also set to NoData. Since there were quite many pixels with values of 0 (dark areas, mostly shadows or water), this would have a significant effect on the further processing of the image and would cause visual noise in the image. That is why at the end the raster was clipped to a rectangular shape to avoid this problem.

2.2.3. Geometric/ Projection Correction

The image under study was projected into UTM projection to the respective UTM zone and georeferenced to WGS 84 datum.

2.3. Image Segmentation

Different object-based image analysis software provides different algorithms for image segmentation. The selection of the algorithm depends on the application and the goal of the segmentation process. In study, we used mostly Chessboard Segmentation, Multiresolution Segmentation and Spectral Difference Segmentation algorithms, which is given below.

2.3.1. Chessboard Segmentation

The Chessboard Segmentation algorithm one to simplest algorithms in object-based image analysis software, splits the pixel domain or an image object domain into square image object. A square grid, which is aligned to the image left and top borders of fixed size is applied to all objects in the domain. Each object in the domain is cut along these grid lines.

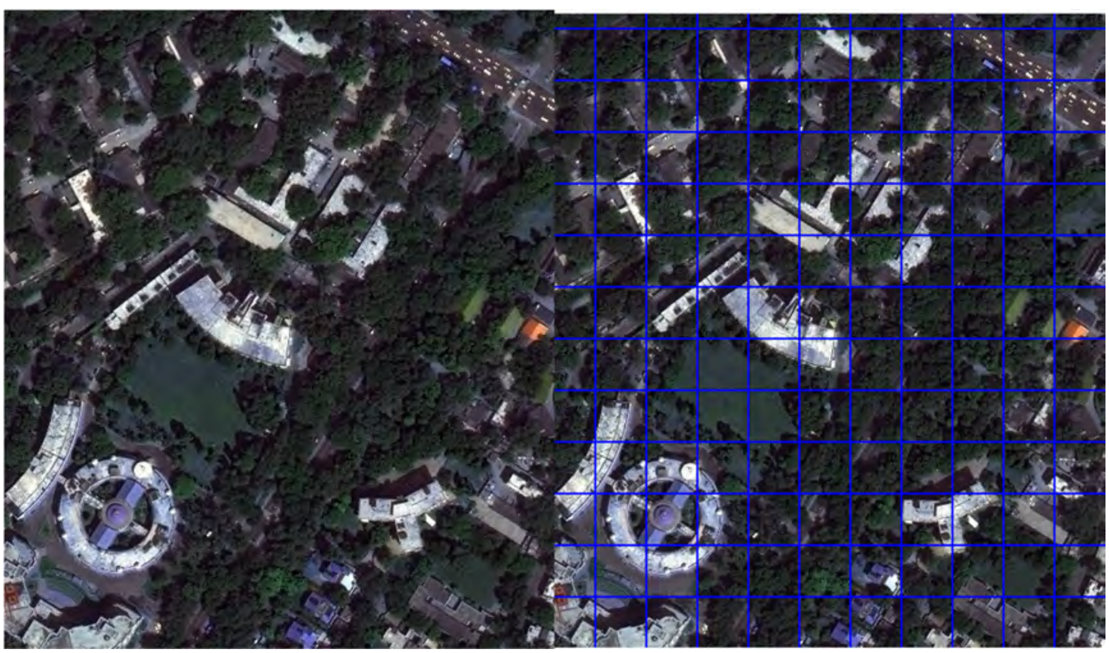


Figure 3 Result of chessboard segmentation algorithm on a VHR image

One of the uses of this algorithm that it allows the incorporation of additional thematic layers in the segmentation process which leads to segmenting an image into segments defined by the thematic layers. The thematic layer used for segmentation will further cause splitting of image objects, hence enabling consistent access to its thematic information. The final resulting image objects will have a proper intersection between the thematic layers **(eCognition, 2018).**

2.3.2. Spectral Difference Segmentation

The Spectral Difference Segmentation refines existing segmentation results. In this algorithm, the image objects which were produced by previous image segmentations, are merged spectrally to similar image objects.

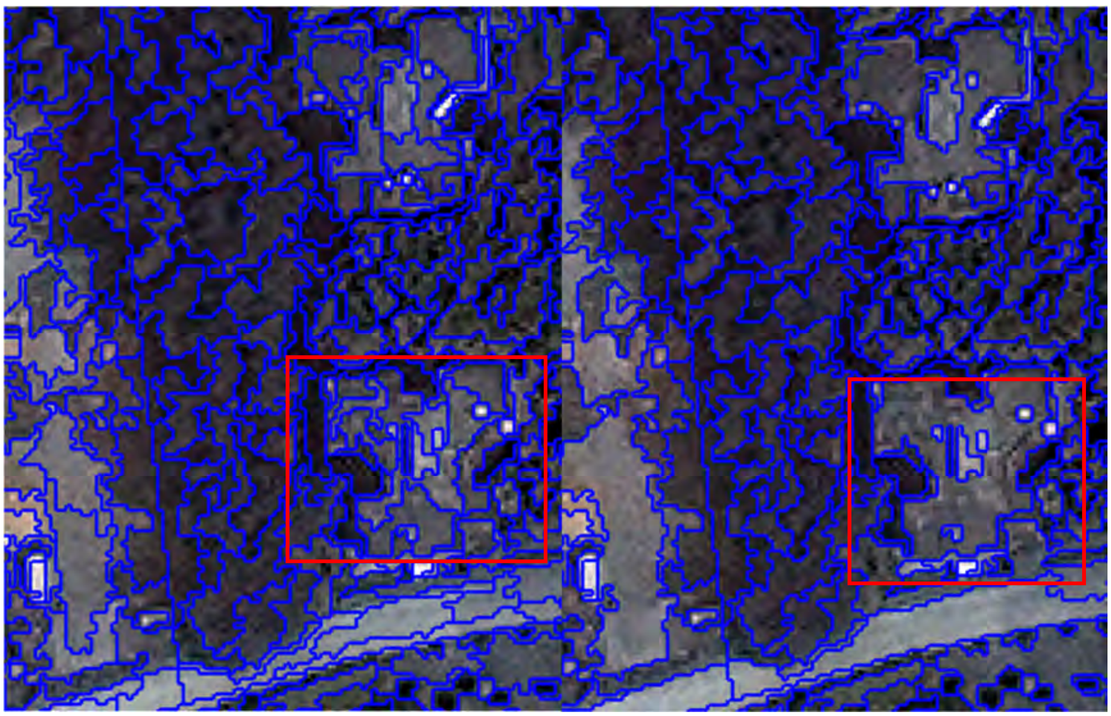


Figure 4 Result of spectral difference segmentation algorithm on a VHR image

The image objects merged with neighboring image objects using their mean spectral values. Image objects in neighboring are merged together if the difference between their spectral mean values are below the value given by the maximum spectral difference parameter set by the user **(eCognition, 2018).**

2.3.3. Multi-resolution Segmentation

The Multiresolution Segmentation algorithm is an optimization procedure. This algorithm minimizes the average heterogeneity and maximizes their respective homogeneity for a given number of image objects. It is executed on an existing image object level and generates image objects at its sub-level or super-level, or in case of pixel on an initial pixel level for creating new image objects on a new image object level. The algorithm merges image objects or pixels. It is therefore a bottom-up segmentation algorithm which is based on a pairwise region merging technique.

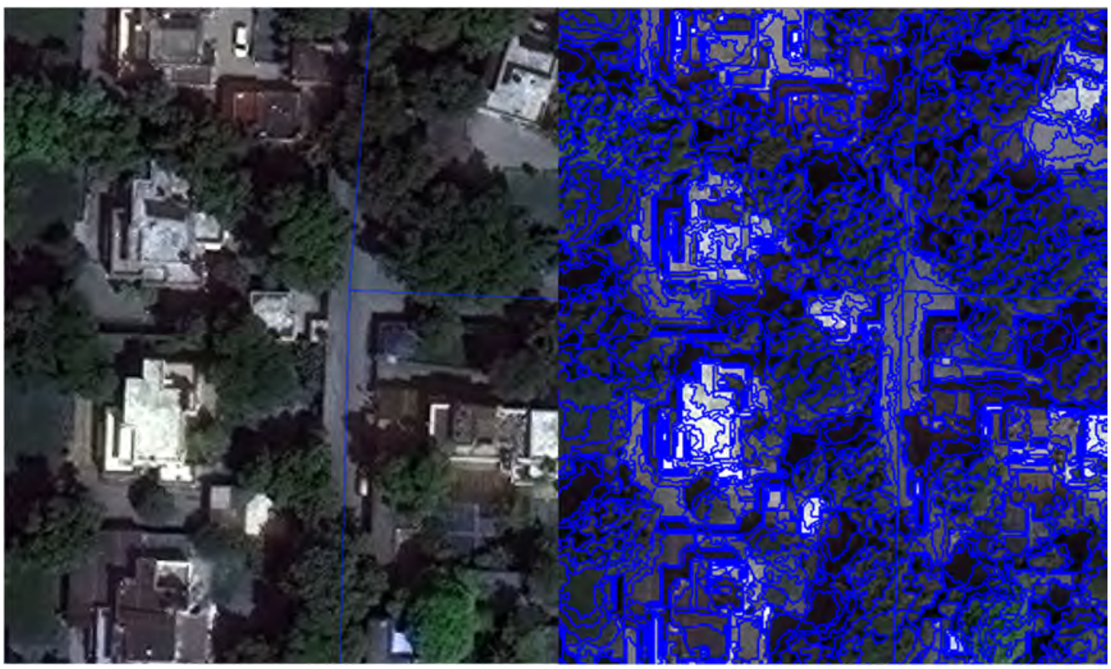


Figure 5 Result of multi-resolution segmentation algorithm on VHR image

The important parameter of this algorithm is the scale parameter which is an abstract term. It determines the maximum allowed spectral heterogeneity for the resulting image objects. The scale parameter determines output size of the resulting image objects. The higher the value of scale parameter the bigger will be resulting image object in size. The given scale parameter of a resulting image objects for heterogeneous data will be smaller than in more homogeneous data. The Scale parameter refers to the object homogeneity.

It is composed of three internal parameters such as color, shape and compactness **(eCognition, 2018).**

2.4. Type of Spectral Indices

There are several spectral indices and image operators which are calculated on the VHR images to be used either in the segmentation process or in the classification process in further steps while perform object based image analysis. Some of these indices highlight certain surfaces like vegetation, built-up surfaces or water bodies, and by applying certain thresholds on these images to images objects can be classified on these surfaces, others may highlight the edges of objects which can be used to guide the delineation of objects in the image segmentation.

2.4.1. Normalized Difference Water Index (NDWI)

The Normalized Difference Water Index (NDWI) is a spectral index, which highlights the presence of open water features in a remotely sensed digital imagery. The NDWI is also used as a metric for masking out black bodies such as water and shadows. This index makes use of reflected near-infrared radiation and visible green light to enhance the presence of such features and suppressing soil and vegetation features. In a study by **Gao (1996)**, another version of NDWI that uses short-wave infrared (SWIR) which is mostly used for monitoring changes in water content of leaves. In this study NDWI is used to classify water bodies. The NDWI formula is:

NDWI = (GREEN - NIR)/ (GREEN + NIR)

2.4.2. Sobel Edge Operator

Sobel operator was computed for the VHR image to identify the edges of features. This operator performs a 2D spatial gradient measurement on an image, and therefore emphasizes regions of high spatial frequency that correspond to edges of features (Woods R. & Gonzalez R., 1992). The created image layer was then used as a thematic layer in the Multiresolution segmentation algorithm in order to segment the image along feature edges. It was also used later for classifying built-up areas, since building edges are characteristic for built-up areas, or for identifying homogenous flat surfaces (with no edges), such as water bodies or bare soil. The result of Sobel operator is shown (sample subset area Shenzhen).

Sobel operator is used to identify the edge features in the VHR image. This operator emphasizes regions of high spatial frequency that correspond to edges of features and performs a 2D spatial gradient measurement on images **(Woods R. & Gonzalez R., 1992)**. The image layers generated from the Sobel operator was then used as a thematic layer in the multi-resolution segmentation algorithm to perform segmentation of the image along feature edges. The created image layer was also used for classifying built-up areas and identifying homogenous flat surfaces such as water bodies or bare soil.

2.4.3. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a very commonly used vegetation index in land cover image analysis, which highlights the areas with vegetation. In the literature NDVI has been widely used to separate vegetation from non-vegetated areas. NDVI formula is:

$$\mathbf{NDVI = (NIR - RED)/\ (NIR + RED)}$$

where NIR and RED are the mean values of all pixels in the boundary of each object in the image in a Near Infrared Band and Red band. The index values range from -1 to 1. High values of NDVI show presence of healthy green vegetation and the lower values might indicate bare soil, stressed vegetation, impervious artificial surfaces and very low values show water bodies. In this study NDVI has been later used for classification of vegetated surfaces.

2.5. Built-up Density Classification Approach

In this master thesis, an approach for creating built-up area units for the calculation and classification of built-up density has been developed. The approach consists of multiple steps such as image segmentation, land cover classification, enhancing classification, extracting built-up area, refining the shape of built-up area of image object growing algorithm, refining the results and calculating the built-up density area on the resulted area segments. The whole procedure and approach such as input data, spectral indices, feature calculation, algorithms use and creating of image object level hierarchy has been explained in the process flow diagram.

2.6. Rule-set Development

A discussed earlier, the main aim is to develop a knowledge base for semi-automatic classification of built-up density within built-up blocks, that is transferable (for one scene to another) and with some minor helpful changes or manual corrections to other image scenes. In order to get this, the first task is to define the extent of these built-up blocks, which could be either some administrative units (land parcels, block enclosed by road segment or other line network, or define by other criteria. However, working with these kinds of pre-defined areas could result into having blocks where half of the area is densely built-up and other half is not built-up at all, but resulting into overall built-up density of 50% for the whole block. The aim here is to define these blocks in a way that the built-up density is uniform throughout the block. Therefore, at first, image segmentation (division of something into smaller parts) algorithm must be applied and the result must be refined to create image pieces/parts representing built-up blocks with uniform built-up density. The rule-set was at first developed on the subset of Shenzhen city (China) study site and later tested transferability to the second image scene WorldVIew-2, New Dehli (India) study site.

2.7. Methodology

Object based-image analysis (OBIA) technique is developed due to increase in spatial resolution and availability of high-resolution images (VHR). The pixels are not analyzed in this approach but rather group of pixels called image object which are a result of segmentation. Segmentation is the process to in which the classification is done using spectral features, shape, texture and contextual information **(Hofmann P., 2004)**

OBIA approach is the ability to analyze image at a different hierarchical level which is created by the segmentation process. The segmentation algorithm can be applied to pixel level to create the first image object or an existing image object to refine to create sub-level. In this process, different level of image object is in the same hierarchical level and are aware of each other and know their hierarchical relationships.

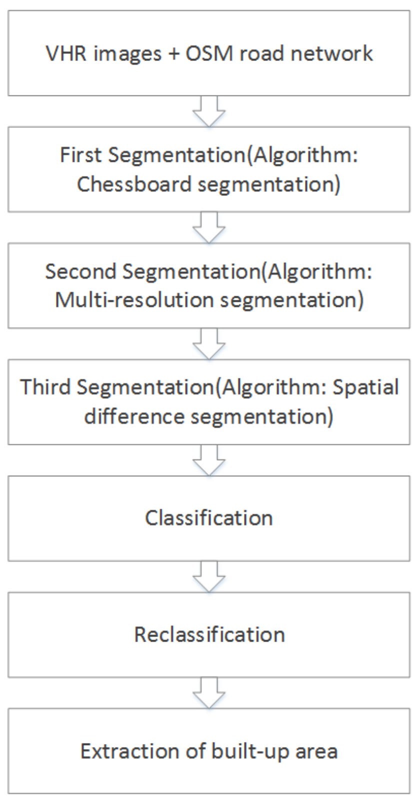


Figure 6 Flow diagram represents approach for built-up density classification

2.8. Software

The software that is used in this study is call eCognition Developer. eCognition Developer is a powerful software that has packages and can be used in development environment for object-based image analysis. This software is widely used in earth sciences to develop rule sets for the automatic analysis of remote sensing data. eCognition Developer can be used for all common remote sensing tasks such as feature extraction, change detection, vegetation detection and mapping and object recognition.

The object-based analysis approach can be used for all common data sources ranging from medium to high resolution satellite data and high to very high- resolution aerial photography. For Lidar, radar or hyperspectral data analysis we can use this software package **(eCognition, 2018)**.

The language that is used in eCognition Cognition Network Language to create rule sets that are the knowledge base for the image analysis. The rule sets are normally developed using graphical environment which ensures rapid prototyping as well as iterative development of applications.

ArcGIS software was used for GIS data management and manipulation. It was also used for creation of reference data for accuracy assessment and for creation of final map visualizations.

MS Excel was used for performing some calculations and creating tables for this document.

Chapter-3

3. Processes and Results

In this part of the thesis all the procedures, analysis and final results of the work are presented and described. The first part discusses the implementation of methodology and in the second part results of land cover classification, including classification accuracy assessment, several statistics for each class are calculated, and in the second part an approach and results of accuracy assessment of built-up density classification is discussed.

3.1. Implementation of the Methodology

As mentioned earlier the approach consists of multiple steps such as image segmentation, land cover classification, enhancing classification, extracting built-up area, refining the shape of built-up area of image object growing algorithm, refining the results and calculating the built-up density area on the resulted area segments. The whole procedure and approach such as input data, spectral indices, feature calculation, algorithms use and creating of image object level hierarchy has been explained in the process flow diagram

Figure 7 Process flow diagram demonstrating the approach and steps for built-up density classification

3.1.1. First Step – First Segmentation (ROAD_NETWORK Level)

Streets, roads and highways often represent the boundaries of built-up areas of different types in an urban environment, and built-up areas within these boundaries tend to be of similar urban fabric. The aim of this study is to find and extract these typical built-up areas. The first step of the rule set is to segment the scene into blocks encompassed by the street network. The Chessboard Segmentation has been used for this purpose in combination of OpenStreetMap vector road network as an ancillary thematic layer. The object size parameter greater than the size of the biggest object in the scene (e.g. 1000000). The result would be the segmenting the image according to the road network thematic layer.

Figure 8 Result of first segmentation - Chessboard segmentation using OpenStreetMap road network on ROAD_NETWORK level

3.1.2. Second Step – Second Segmentation (LAND_ANALYSIS Level)

The most important step to extract built-up surfaces from the images is to delineate them as correctly as possible and distinguish from other surfaces using segmentation. To further process the already segmented image another subsequent segmentation has been performed on the 1st image object level (ROAD_NETWORK level). Multiresolution Segmentation has been applied because it has the best capabilities to delineate features. In this step, the OSM road network layer was used again as an ancillary thematic layer to keep the resulting segments within the constraints of the road network segments of OSM. Multiresolution Segmentation algorithm has the capability to assign weights to individual image bands to give more importance to certain bands information in the image dataset.

The aim of multi-resolution segmentation is to differentiate built-up surface from vegetation area. The vegetation features have strong reflectance values in near infrared (NIR) band, NIR band was assigned higher weights to differentiate both built-up area and vegetated surface. The calculated NDVI band was also assigned weight of 5 to help delineate built-up features from vegetation. Sobel edge layer which was calculated using a sobel operator was assigned also a weight of 5 because building edges are more prominent than edges of trees or other vegetation. This operator also helps to delineate built-up features. The scale parameter was set to 20 because the target building objects small. The shape parameter was set to 0.8 and the compactness parameter to 0.2. The result is show below.

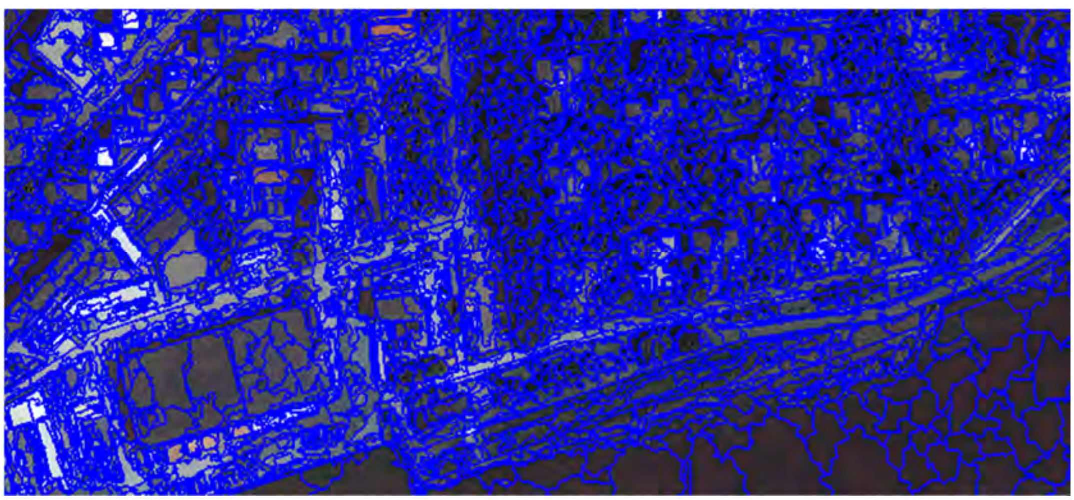


Figure 9 Result of second step – Multi-resolution segmentation and creation of LAND_ANALYSIS level

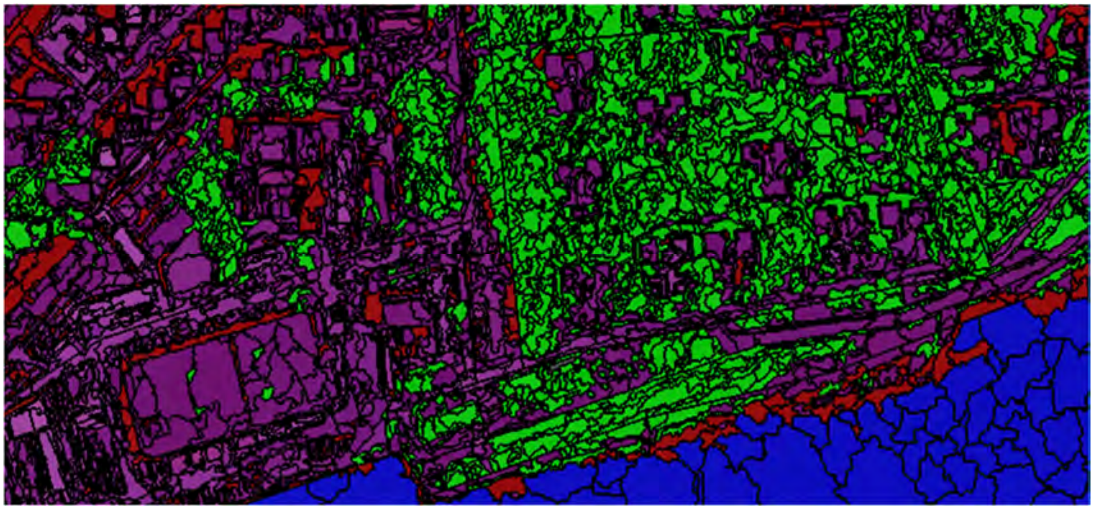
3.1.3. Third Step – Classification of Image Objects

In this step image objects were classified into several land cover classes to extract built-up area. Since the complex detailed land cover classification is not the aim of this project, but it is important to distinguish built-up areas from other surfaces such as vegetation or water. The information about other classes has been used later in adjusting the shape of image objects in order to the find optimal shape representing a segment with uniform built-up density. Different spectral, spatial, textural or contextual features has been employed in the classification rule set creation to classify image objects into land cover classes. Several normalized indices such as NDVI, NDWI or Sobel Operator using different band combinations were examined to suitably extract built-up land.

Water has been classified according to values in the NIR, NDVI and NDWI. Often this class is spectrally very similar to the shadows, so different features were used to separate these two spectrally similar classes. The Sobel edge layer has been used to eliminate any surfaces with strong edges from the water class. Shadows has been also classified based on the values of NIR band. Standard deviation in NIR band of the image object was used to separate it from water. Water surface is normally more homogenous having lower standard deviation values than shadows, where different objects such as cars, trees, etc can still often be seen in the image.

Class	Image object feature and parameters
Built-Up	Mean red >100 NDVI < 0.25
Vegetation	Mean red < 110 NDVI > 0
Water	Intensity > 78 Mean NIR < 75 Mean Sobel Operator <3 Standard Deviation NIR < 7
Shadows	Brightness < 350 WVI > 1.8

Table 3 Image object features and parameters have been used to classify different image objects for Shenzhen city study site



(**color:** purple=built-up, green=vegetation, blue=water, red=shadow, no color=unclassified)

Figure 10 Result of third step - Classified image objects at the LAND_ANALYSIS level

3.1.4. Fourth Step – Third Segmentation (SPECTRAL DIFFERENCE level)

Once the classification in the above level completed, the image object level must be refined to get the targeted result. The classification resulted in certain surfaces namely vegetation, water, shadows and built-up areas (including houses, buildings, roads, parking lots, infrastructure, and other man-made urban objects). The spectral difference algorithm has been used to merge neighboring image objects having similar spectral properties on resulted in a new image object level, which reduce the number of image objects in the image scene. This algorithm allows merging of several smaller image objects that normally does not represent anything meaningful in reality into larger image objects that often represent larger real-world objects. Often bare soil has a similar spectral response to built-up objects. To get better result it is necessary to implement other than spectral reflectance-based rules which distinguishes bare soil from built-up class.

Different textural features have been considered, one of them is the standard deviation (Std.) in NIR. Homogenous surfaces such as bare agricultural land has been represented by one compact image object which offered a possibility to use the area feature of these image objects to distinguish them from urban built-up surfaces. Built-up surface object is usually not as big and homogenous as agricultural, bare soil fields which means that the image objects which are very large and also relatively homogeneous thus has been classified as bare soil.

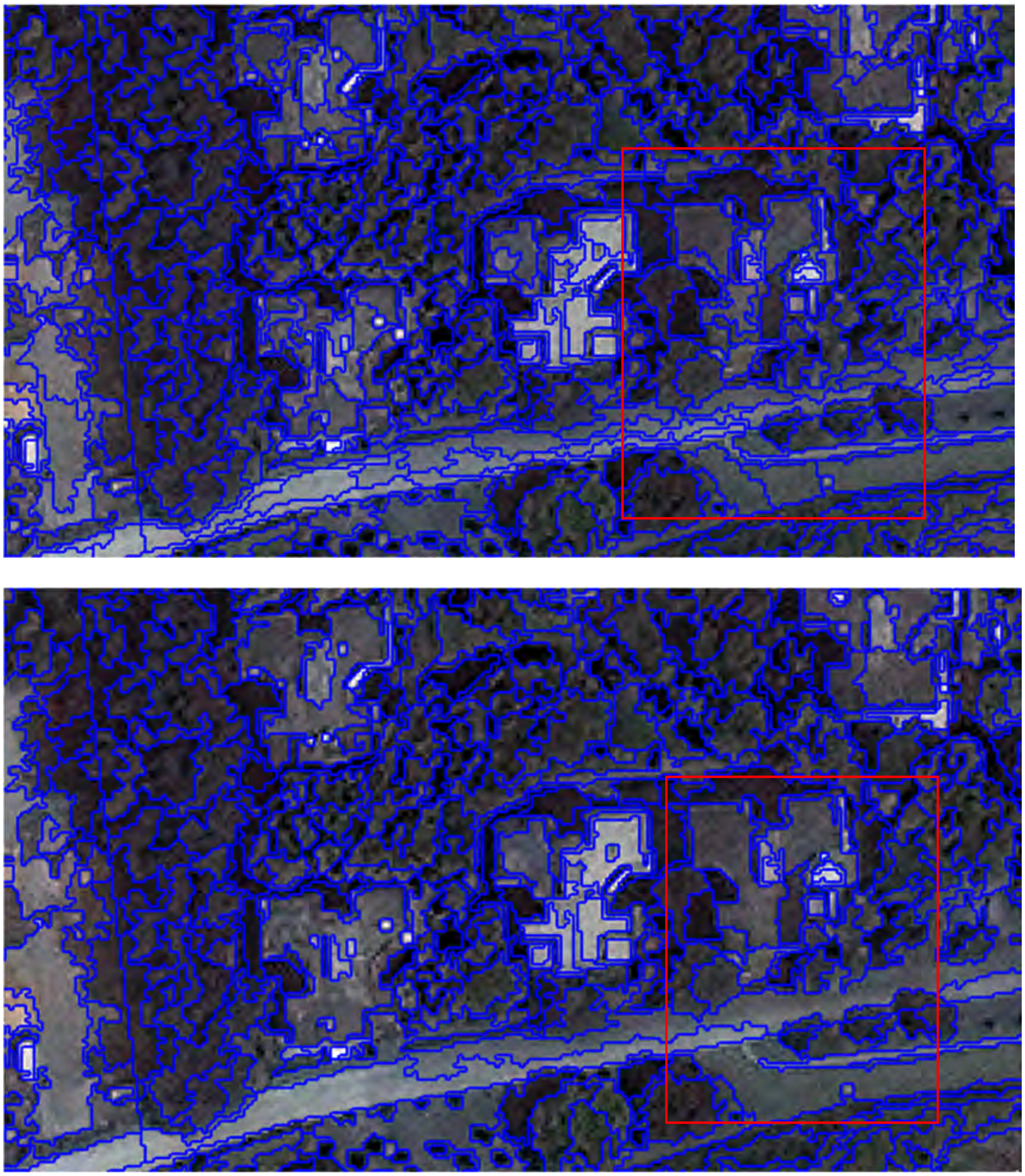
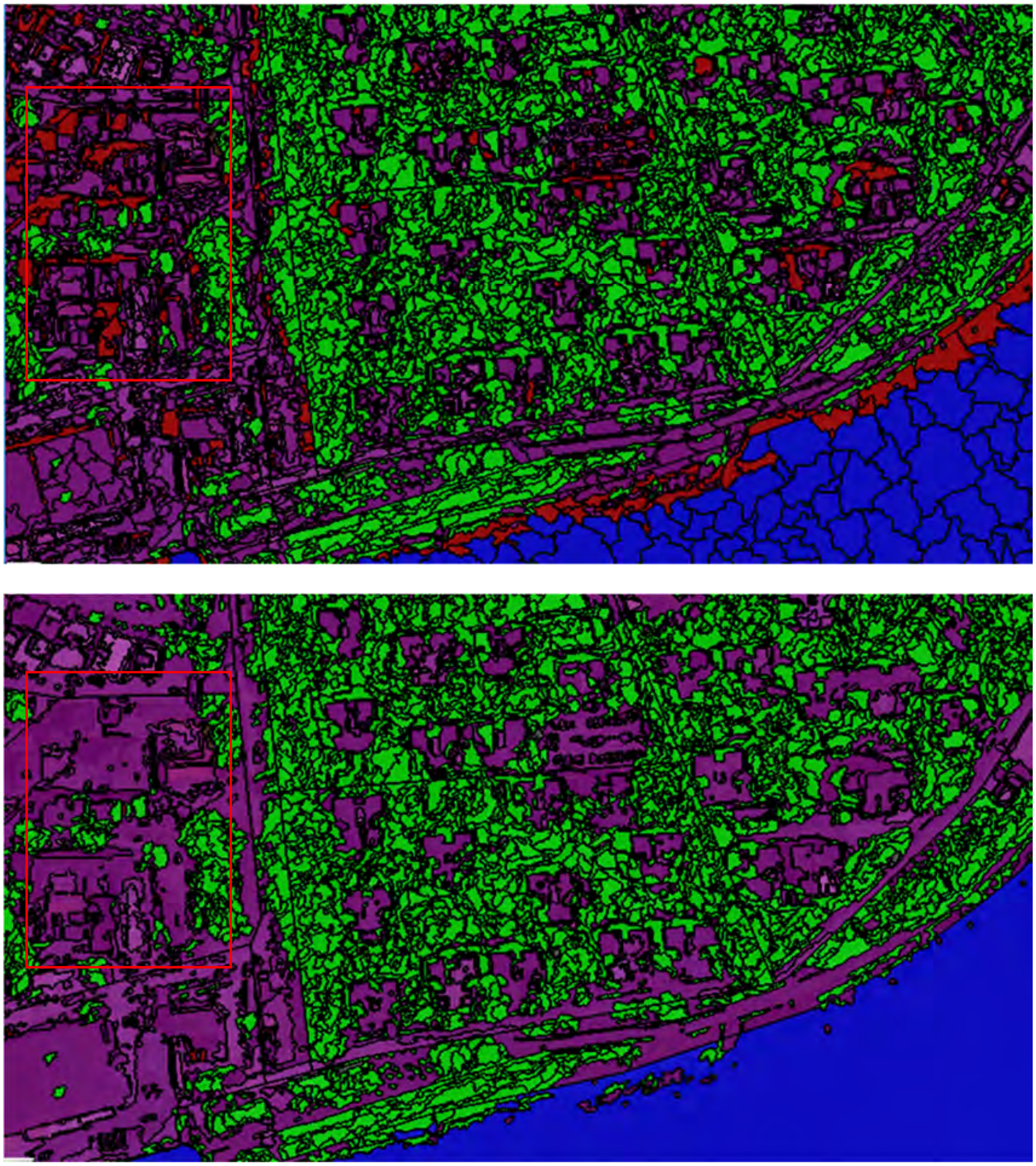


Figure 11 Result of fourth step - Spectral difference segmentation merging (SPECTRAL_DIFFERENCE level)

3.1.5. Fifth Step – Reclassification of Existing Image Objects

In the this step the image objects were reclassified and assigned to different classes in order to correct the first classification errors. The aim of reclassification is to bring the land cover image representation the closest possible to the reality. In the last step, after the classification was completed the resulted built-up class excluded the shadows in the built-up classification because the built-up areas in the shadows have lower reflectance values in all bands. Since the shadows are not real physical surfaces and they may change over time with the angle of the Sun, and they should not be mapped. They should be reassigned to their neighboring classes where they most likely belong to as shadows. Shadows that are near built-up areas most likely belong to other built-up areas, such as lower buildings road, parking lots and other infrastructure objects. Based on the above assumption, the image objects that classified as shadows which were very close to built-up image objects, has been reclassified into built-up class. The reclassification has been done using class related features that include distance to image objects of built-up class or common border with image objects. In this step some surfaces possibly swimming pools has been classified and assigned different class rather to the water class because since they also represent water bodies. Swimming pools have different spectral response. Swimming pools were classified separately, because they did not match the classification criteria for the water class. The aim of this study is not to create a land cover map, but the focus is built-up areas, In the end the two thematic classes were merged together. In order to exclude these surfaces from the built-up class, swimming pools were considered and classified separately.

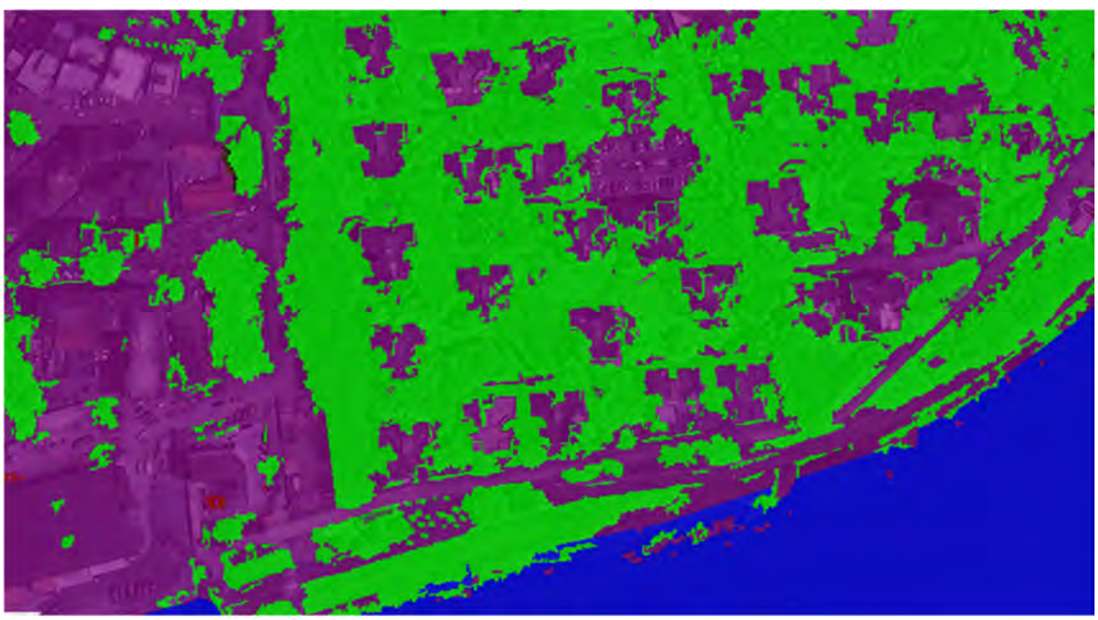


(**color:** purple = built-up, green = vegetation and blue = water)

Figure 12 Result of fifth step – Reclassification of existing image objects

3.1.6. Sixth Step – Land Cover Map Generation (LAND_COVER Level)

After using image object features and implementing rules to classify the surfaces, a land cover map layer has been produced. In the rule set, in order to distinguish it from other analysis levels and for later referenced during the built-up density calculation this land cover map layer has been copied to a separate image object level (LAND COVER Level). As mentioned earlier that a complex land cover map layer was not the main aim of this project, but rather a by-product, because the focus was on extraction of built-up surfaces (including houses, buildings, roads, parking lots and other urban structures), it was important to reliably classify these surfaces, and relations with neighboring and other classes was used for this purpose. Also, later during the refinement of the shape of built-up layer, for the purpose of generalizing and better representation of compact built-up area, information about neighboring classes was used to reinforce layer growing restrictions. The land cover map represents four main classes: built-up area, vegetation, water.



(**color:** purple=built-up, green=vegetation, blue=water)

Figure 13 Result of sixth step - Land cover classification on LAND_COVER image object level

3.1.7. Seventh Step – Built-up Extraction and Refinement

In this step the LAND_COVER image object is generated and the built-up class has been extracted and saved on a separate image object level. The built-up area has been considered and used for further processing. The built-up area has been extracted to separate layer (BUILT layer). The rest of the class have been classified as unclassified except water class. Water class has been used to prevent growing of built-up layer into water bodies. After having a layer that represents the built-up area, out next task is to refine and generalize its shape to better represent the compact built-up area. Once we get the final layer it would be more usable as a GIS layer.

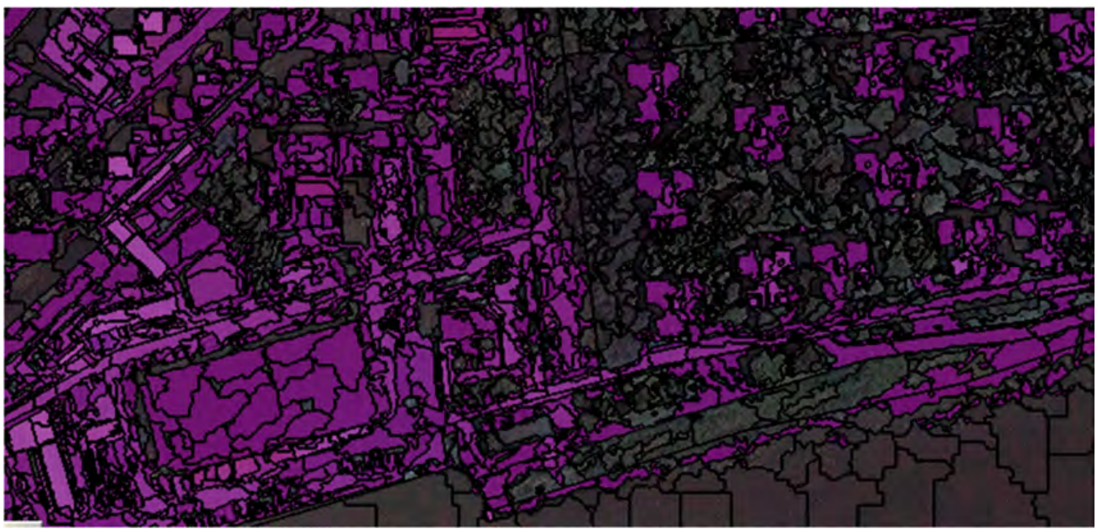


Figure 14 Result of seventh step - Built-up extraction (purple = built-up, no-color= non-built-up)

3.1.8. Refining the Shape of Image Objects

The image objects from the step above at the BUILT level have been further refined to get the optimal shape which represents extended continuous urban area and would be used for built-up density calculation. The morphological operators such as dilation have been used to achieve this.

3.1.8.1. Pixel Based Object Grow – Dilation

The two of the basic operators in the area of image processing morphology are called Dilation and erosion respectively. Dilation is typically applied to binary images which has the basic effect on a binary image that gradually enlarges the boundaries of regions of foreground pixels. The areas of foreground pixels grow while holes within regions become smaller in size **(Woods R. & Gonzalez R., 1992).** When adding new layers of pixels to the foreground the sharp edges of the image objects get it smoothened. Dilation is also known as a pixel-based buffer, where the number of pixel layers is specified instead of specifying a buffer distance. We can select a certain class as foreground image, in our case we have selected the built-up area. When extracting the built-up area on a separate level, we get a binary image having values of built-up = 1 and unclassified = 0. In our software package eCognition the dilation is implemented in pixel-based object resizing algorithm if grows called dilation or shrinks called erosion the image. The algorithm is implemented on image objects as binary image foreground a specified number of times by adding one-pixel layer around it every time.

The algorithm can be also used to smooth the surface of image objects by growing or shrinking the edges. In order to implement the refined technique on the shape of built-up area the built-up class was copied on a new level in our case REFINE_Level. The dilation of 15 pixels was applied to the entire built-up layer using pixel-based object resizing dilation algorithm. The parameter value of 15 in grow algorithm has been was chosen after several tests with several other numbers.

The parameter value selected allows merging image objects which are relatively close to each other to one continuous image object in further subsequent steps. The resultant image represents the whole local built-up area and also significantly generalizing and smoothing the rugged shapes of built-up layer which were the result of Multiresolution segmentation and classification of built-up surfaces. The parameter value is user-defined and has to consider the image pixel size (0,5 m) and the local urban typology and morphology.

3.1.8.2. Fusing Small Islands

The resulting image objects grew in size after applying 15 pixels grow value in the parameter of the REFINE level. The unclassified pixels consist of vegetation, bare soil except water. This grow was constrained by the OSM road network, they could only grow until they reach to the edges. There are some very small areas left, which were not covered by the grow operator. They were excluded from the layer and were unclassified. The areas that are smaller than 1000 pixels are surrounded by BUILT-UP Layer. The small and unimportant areas in the middle of continuous built-up area has been fused with BUILT_UP class, which generalizes the BUILT_UP layer and makes it more representative.

3.1.8.3. Merging Resulting Objects

In the last step of object refinement, the neighboring image objects that have been created by pixel based object grow are merged together considering the constraints of the boundaries of the road network. The reason for this method is to get fewer, larger and more representative shapes of continuous built-up area rather than many smaller image objects representing individual buildings.

3.1.9. Eighth Step - Built-up Density Classification

The layer on the REFINE level now represents slightly buffered built-up areas across the whole image scene after applying pixel-based object resizing for grow, generalization and smoothing of built-up layer. The image objects represent compact built-up areas inside the OSM road boundaries. The next step is to calculate the amount of built-up class from the previous step of LAND_COVER level, which represent the actual distribution of built-up land cover excluding the vegetation, water and bare soil portion of the image. A relative area of sub-object has been used for this calculation. The image object feature which is an area covered by sub-objects from the specified image object level assigned to a given class divided by the total area of the image object.

The sub-objects level is actually the downward distance of image object levels in the image object hierarchy between the image object concerned and the sub-objects level. These segments have been classified into several discrete classes. These classes are the amount of built-up area on the Land Cover Level which they are consisting. The built-up density classes have been defined in following ranges:

- 0-10% = non-built up areas
- 10-50% = sparsely built-up to openly built-up areas
- 50-90% = openly built-up to densely built-up areas
- 90-100% = completely built-up (or sealed) areas.

Figure 15 Final result - Built-up density classification on the refined BUILT layer (ROAD_NETWORK Level and ACTUAL_BUILT-UP_DENSITY Level)

3.2. Results

3.2.1. Output Layers - Image Object Level Hierarchy

Image object level hierarchy consists of several image object levels has been created during the development of image analysis process in eCognition Software packages. Every level represents different objects or classes and have relationship with super or sub-objects defined. The table below describes the image level hierarchy.

Output Layers	**Description**
ROAD_NETWORK level	Image segmented into blocks created by road network
ACTUAL_BUILT-UP_DENSITY level	Level closely representing the overall shape of compact built-up area used for built-up density classification
REFINE level	15px buffer on built-up level – grow, generalization, smoothing
BUILT-UP level	Only built- up layer
LAND_COVER level	Abstracted land cover – built-up, vegetation, water
SPECTRAL_DIFFERENCE level	Segments representing objects with high spectral homogeneity
LAND_ANALYSIS level	Segments closely representing individual buildings and distinct features, scale level 20

Table 4 Image object level hierarchy output layers and the description

In the preceding sections we will do some analysis of the rule-set resulted classification and perform the accuracy assessment of generated classification of the levels LAND_COVER, BUILT_UP Density (at ROAD_NETWORK Level and ACTUAL_BUILT-UP_DENSITY Level).

3.2.2. LAND_COVER Level (Classification Results)

3.2.2.1. Land Cover Classification and Statistics

The rule-set (classification process) was designed to identify four main classes such as built-up, vegetation, water. The intermediate extra classes such as shadows was produced in the process. These classes were fused into other classes in the next steps and finally the land cover map with four main classes at LAND_COVER image object level was generated. The land cover statistics have been calculated for the resulting land cover map in the subset selection area part of the study site such as total area and relative area of each class to illustrate the result quantitively and see the portion of each class in the whole area.

Land cover statistics – Shenzhen city		
Class	**Area (ha)**	**Area (%)**
Built-up	219	78
Vegetation	57	20
Water	6	2
Total	282	100

Table 5 Land cover area statistic - Shenzhen city study site

In the Shenzhen city study site (subset selection) built-up was the dominant class identified with over 78% share. The main focus of the classification process and the rule-set development was to classify the built-up area as accurately as possible. The built-up class was the most important class in the whole classification process, because it was extracted and processed further to generate representative shapes of the continuous built-up area. The purpose of the other classes was classified to minimize the omission and commission errors of the built-up class. The information about other than built-up class was useful in setting up the class related rule-sets and the constrains in the refinement process. There were some image objects that did not fulfill the criteria of any class were left unclassified. These classes were mostly shadows outside the urban area, or mixed artificial surfaces which somehow did not fulfill the conditions of any class inclusion criteria. The vegetation class was up to 21% which included all kinds of vegetation, including shrubs, trees, grasslands or crops in agriculture fields. The agriculture land with low sparse vegetation was also classified into vegetation class. Another dominant class was water with almost 2% due to the presence of river in the study site.

3.2.2.2. Accuracy Assessment

Once the land cover classification is completed and the land cover map is created an accuracy assessment is performed to check the quality of the land cover classification result. The reference points for each class were collected by the visual interpretation of the original VHR image. The points were distributed throughout the entire scene. The total of 100 reference points was collected for vegetation and built-up area and 50 points for the water class because the portion of water class on the whole image was much lower in comparison to other classes. Standard classification confusion matrix was produced for the land cover map and the Overall accuracy were calculated as shown in the table below.

Shenzhen city land cover classification - confusion matrix				
User Class \ Sample	**built-up**	**vegetation**	**water**	**Sum**
Confusion Matrix				
built-up	104	7	1	112
vegetation	8	71	7	86
water	0	0	51	51
Sum	112	78	59	0
Overall Accuracy	92.85%			

Table 6 Confusion matrix for Land Cover classification - Shenzhen city study site

The above confusion matrix for the land cover classification show that 92.85% of the reference points that were collected from built-up area were classified correctly as built-up which shows very good result. The result is satisfactory since built-up is the main class of interest in this study. There are several water surfaces that were misclassified as built-up which is because they were at first classified as shadows and then reclassified as built-up in our rule-set. Based on the above observation, we can conclude that built-up area was successfully classified with high accuracy and thus can be used for further refinement and creation of optimal built-up density segmentation.

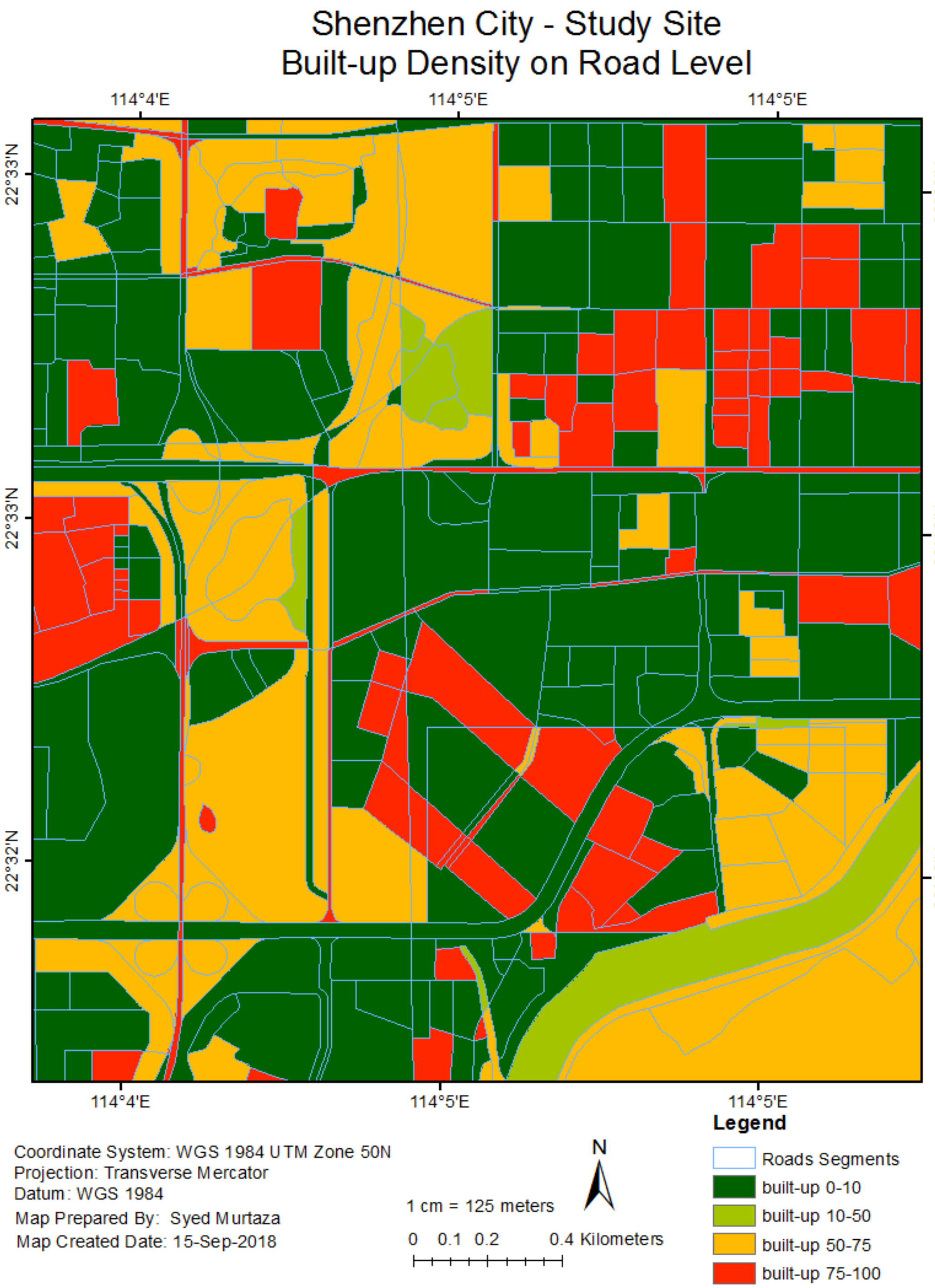
3.2.3. BUILT-UP Density Level (Classification Results)

3.2.3.1. Built-up Density Classification

The portion of built-up area on the whole area segment represent the built-up density. The density unit represents homogenous areas in terms of urban typology and spacing between the building. Built-up density has been calculated at first on level ROAD_NETWORK level and then it was refined at (ACTUAL_BUILT-UP_DENSITY level). The roads often delimit these homogenous areas and the urban typology such as building spacing, size, shapes or other morphological parameters are normally similar within the boundaries. The density classes were designed in four categories: 0-10%, 10-50%, 50-90% and 90-100%. The first category or class 0-10% represents any surface with any little built-up structures having vegetated areas, forest, agricultural land, bare land or water bodies. Roads are used to segment the image scene into these road blocks. The results were later compared to demonstrate the influence of the selected area until the final result of built-up density calculation. The second class 10-50% show sparsely to open built-up area like rural settlement, small gardening houses or residential house with relatively huge space in between them which are found in the suburbs or outer part of the city or in villages. The third class 50-90% shows open to dense built-up areas having some vegetation or small space in between buildings which are found in residential areas of the cities or in the centers. The fourth class ranging from 90-100% represents very dense urban fabric with almost no vegetation or space between buildings such as shopping centers, parking lots or paved squares. These surfaces are also in the built-up land cover class.

3.2.3.2. Built-up Density Classification (ROAD_NETWORK Level)

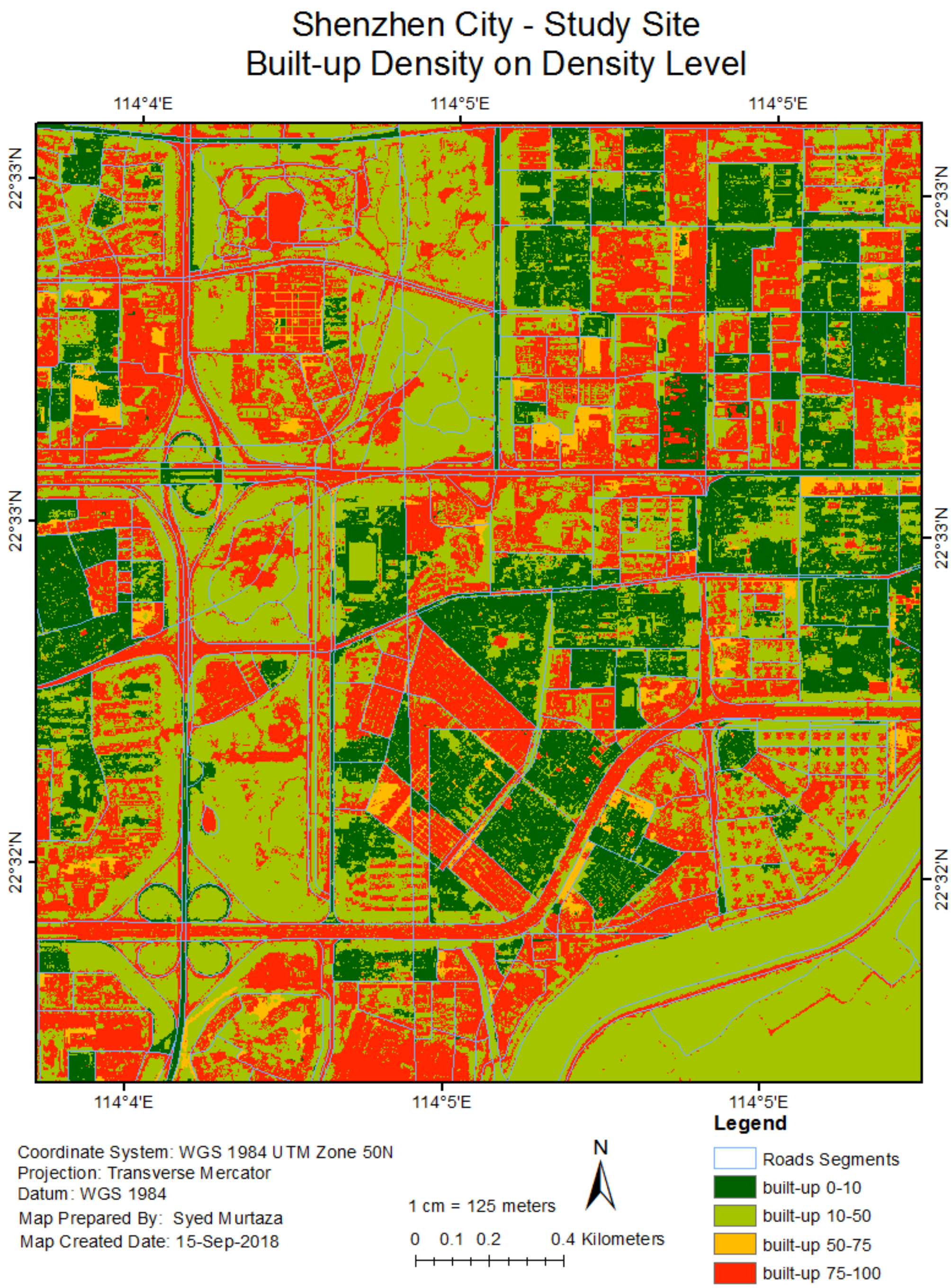
The image segmentation using OSM road network data was created at first. The built-up density as built-up portion of the overall area of the segmentation has been calculated and classified on the segment defined by road boundaries called ROAD_NETWORK level. The result of built-up density classification data and the creation of ROAD_NETWORK level was done by first image segmentation.



Map 3 Result of built-up density classification on ROAD_SEGMENT Level (Study site in Shenzhen city)

3.2.3.3. Built-up Density Classification (ACTUAL_BUILT-UP DENSITY Level)

The successful classification of land cover, especially the built-up areas with convincing accuracy the next step was extracting built-up class and refining the built-up layer by dilation algorithms. The refined image object creation on the ACTUAL_BUILT-UP_DENSITY level was as a result of built-up density calculation which resulted in final built-up density maps. These maps represent classified area segments or units of similar urban fabrics, typology and the portion of actual built-up surfaces within them.



Map 4 Result of built-up density classification on ACTUAL_BUILT-UP_DENSITY Level (Study site in Shenzhen city)

3.2.4. Accuracy Assessment

The quantitative assessment of this built-up density classification is done by digitizing the reference polygons from the original VHR image for each density class: 0-10%, 10-50%, 50-90% and 90-100%. The purpose to design these density classes in these ranges was to allow easy visual identification of the respective density class in the original VHR image.

The reference polygons were digitized using original VHR image and the available reference data. These polygons represented areas having similar built-up density and urban fabric. It is difficult to estimate the exact density number visually because we have four obvious density classes in the classification. The small areas were selected as reference polygons by digitization of VHR image. The land use and land cover map have been used as help for creating these reference polygons. The maps have different land use categories in whole Afghanistan for different land use and land cover and urban fabric classes can be distinguished by different level of built-up density. It may serve as data source for various regional and urban planning studies.

Different sizes and shapes of reference polygons have been created for each density class and then merged together to single dataset. This dataset later converted to raster in order to create one reference thematic raster. This raster was compared to the result of built-up density classification. A confusion matrix is also produced for this classification. The accuracy assessments of both ROAD_SEGNENT level and BUILT_UP_DENSITY level was performed and the result was compared and discussed.

The confusion matrix of the land cover classification was produced for both study sites that show the correctly and incorrectly classified pixels and omission and commission errors.

3.2.4.1. Built-up Density Classification (ROAD_NETWORK Level)

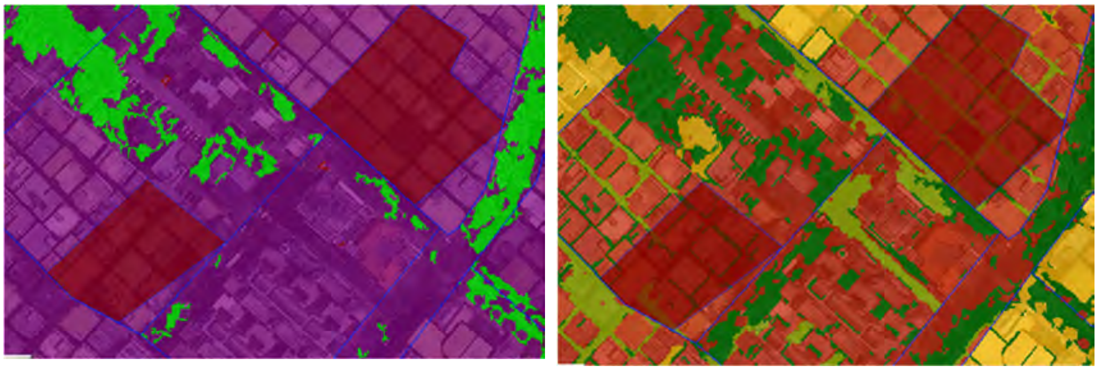
This matrix above shows that most of the 0-10% reference polygons have been classified correctly. These reference polygons must have been the ones that were located in a segment with no built-up area or built-up up to 10% in the whole segment. Some of these 0-10% reference polygons have been classified as 50-90% because there is no built-up area within these reference polygons which are located within a larger segment. This had an influence on the built-up density of whole segment which classify the area under the reference polygon in this range. The problem of calculating the built-up density on large heterogeneous areas is that one number is reported for the whole segment, whereas there might be high variability of the built-up density in the whole segment. The other issue is 10-50% of reference polygons classified as 0-10% which is for 46% of cases which is because the amount of classified built-up area on the overall segment is defined by the road network was less than 10%. The problem might be that the built-up areas in this part of the image were not successfully classified on the LAND_COVER level for some reason.

ROAD_NETWORK level - built-up density classification - confusion matrix										
Built-up density class										
Classes	0-10	%	10-50	%	50-90	%	90-100	%	Total	%
built-up 0-10	894	33%	-	0%	-	0%	-	0%	894	7%
built-up 10-50	1,243	46%	1,634	59%	-	0%	-	0%	2,877	21%
built-up 50-90	574	21%	-	0%	1,708	100%	1,860	29%	4,142	30%
built-up 90-100	-	0%	1,126	41%	-	0%	4,632	71%	5,758	42%
Total	2,711	100%	2,760	100%	1,708	100%	6,492	100%	13,671	100%
Overall Accuracy		**65%**								
Kappa Coefficient		**50%**								

Table 7 : Confusion matrix for built-up density classification on the ROAD_NETWORK level

In the confusion matrix another situation can be observed that reference polygon of 50-90% classes being classified as 10-50% classes which is related to the size of the segment and portion of built-up area inside it. The 50-90% class in the reference polygon is created over small area where it is valid, the whole segment has less than 50% of built-up area and the whole segment is classified as 10-50% resulting in errors in the confusion matrix.

a **b**



c d

a) original VHR image: red polygon = 50-90% reference polygon, green lines=road network
b) built-up density classification on ROAD_NETWORK level
c) land cover classification: purple=built-up, green=vegetation
d) built-up density on BUILT-UP level

Figure 16: Built-up density classification accuracy assessment with 50-90% reference polygon

The class 90-100% represent completely built-up areas was classified as lower density, because the built-up density has been calculated on a larger segment having some non-built-up areas with lower density which decreased the overall built-up density value of the whole segment. In the reference polygon it was classified successfully in the relatively small segments which were homogeneously density built-up. For example, completely sealed parking lot or big compact building or encircled roads. The general problem in classifying built-up density on road network segments is that it only gives good results if the areas within the roads are homogenously built-up. In case of different types of spatial distribution of buildings within this area, then the resulting built-up density indicator is not representative. In some urban environment this approach could work which are densely and regularly built-up like in some dense city centers where not much open space exists and road network is more regular and homogenously built. For the built-up area where not large spaces exist within one segment, this might not give good result.

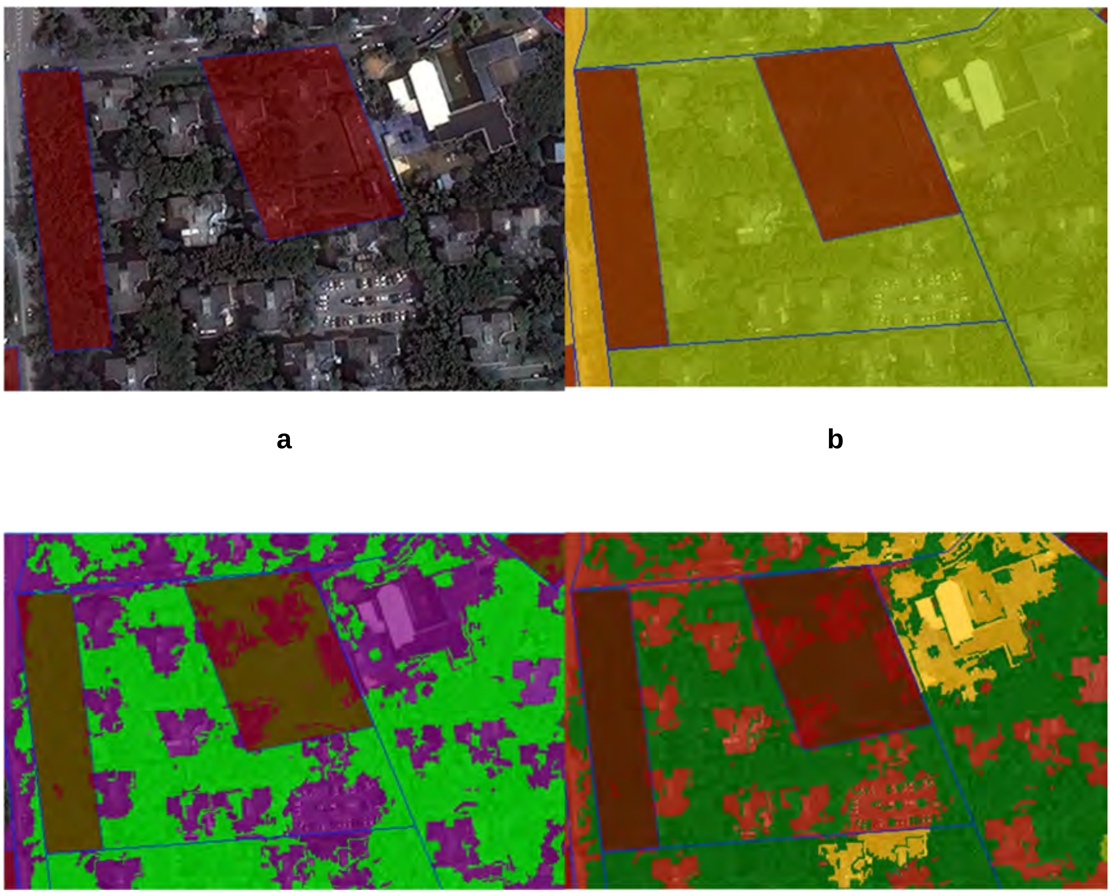
3.2.4.2. Built-up Density Classification (ACTUAL_BUILT-UP_DENSITY Level)

The error matrix for Shenzhen site describes which areas of the reference built-up density polygons were classified correctly by the built-up classification method development, and where confusions between classes occurred. As apparent from the confusion matrix, the non-built-up areas (built-up 0-10%) we classified with high accuracy based on selected reference polygons. This was expected, since it is obvious, and easily interpreted from the original VHR image, which areas are non-sealed (non-built-up). Some small errors occurred at the edges of the reference polygons, where growing of the built-up layer (extracted BUILT layer) caused growing these image objects in the areas of the reference polygons. This matrix above shows that most of the 0-10% reference polygons have been classified correctly. These reference polygons must have been the ones that were located in a segment with no built-up area or built-up up to 10% in the whole segment. Some of these 0-10% reference polygons have been classified as 10-50% because there is no built-up area within these reference polygons which are located within a larger segment. This had an influence on the built-up density of whole segment which classify the area under the reference polygon in this range. The problem of calculating the built-up density on large heterogeneous areas is that one number is reported for the whole segment, whereas there might be high variability of the built-up density in the whole segment. The other issue is 10-50% of reference polygons classified as 0-10% which is for 87% of cases which is because the amount of classified built-up area on the overall segment is defined by the road network was less than 10%. The problem might be that the built-up areas in this part of the image were not successfully classified on the LAND_COVER level for some reason.

ACTUAL_BUILT-UP Density level - built-up density classification - confusion matrix										
Built-up density class										
Classification	0-10	%	10-50	%	50-90	%	90-100	%	Total	%
built-up 0-10	2,008	74%	1,265	46%	317	19%	702	11%	4,292	31%
built-up 10-50	-	0%	992	36%	35	2%	281	4%	1,314	10%
built-up 50-90	3	0%	27	1%	615	36%	306	5%	951	7%
built-up 90-100	694	26%	476	17%	741	43%	5,203	80%	7,114	52%
Total	2,711	100%	2,760	100%	1,708	100%	6,492	100%	13,671	100%
Overall Accuracy	**65%**									
Kappa Coefficient	**46%**									

Table 8: Confusion matrix for built-up density classification on the ACTUAL_BUILT-UP level

In the confusion matrix another situation can be observed that reference polygon of 50-90% classes being classified as 10-50% classes which is related to the size of the segment and the portion of built-up area inside it. The 50-90% class in the reference polygon is created over small area where it is valid, the whole segment has less than 50% of built-up area and the whole segment is classified as 10-50% resulting in errors in the confusion matrix.



a b

c d

a) original VHR image: red polygon = 10-50% reference polygon, green lines=road network
b) built-up density classification on ROAD_NETWORK level
c) land cover classification: purple=built-up, green=vegetation
d) built-up density on BUILT-UP

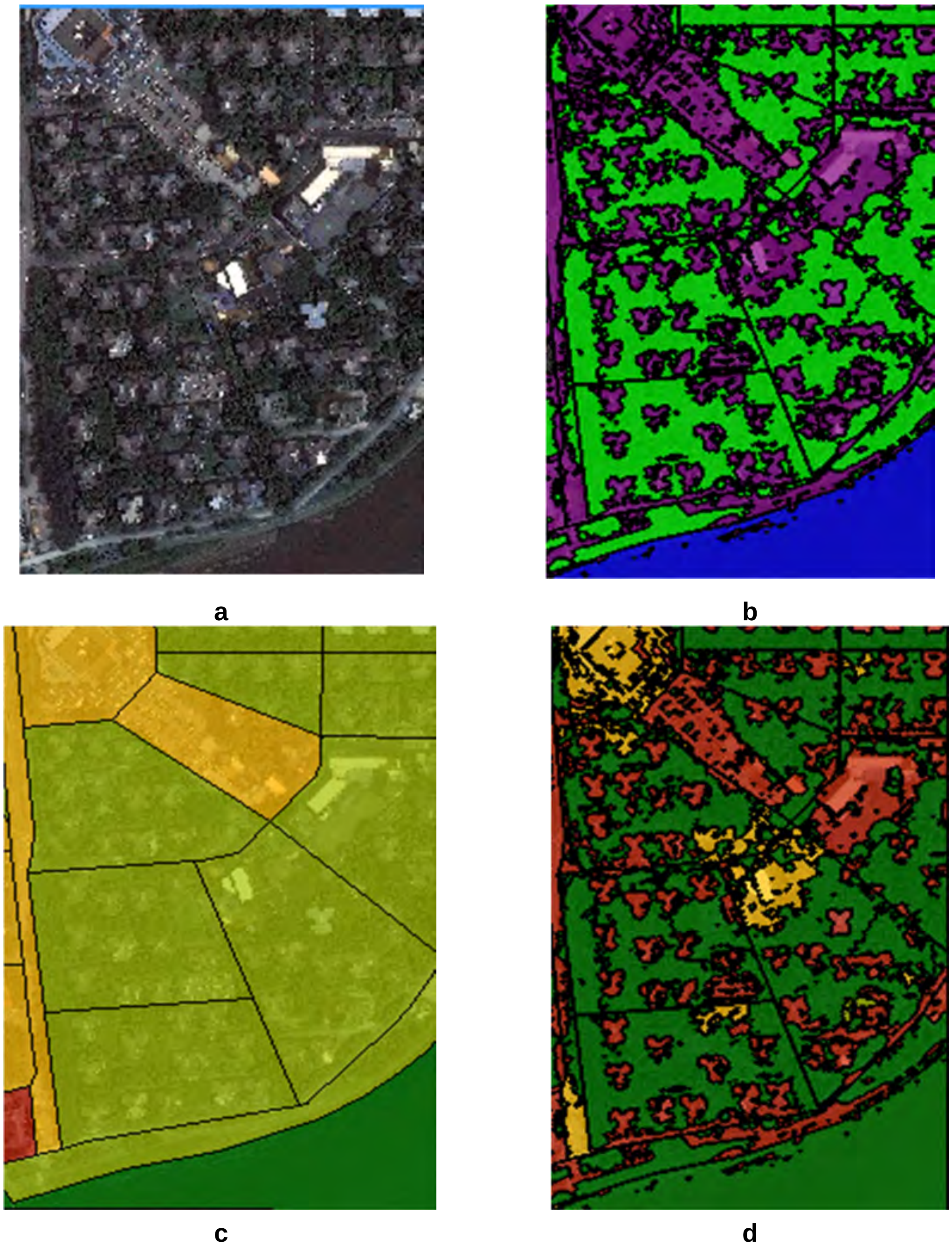
Figure 17: Built-up density classification accuracy assessment with 10-50% reference polygon

The class 90-100% represent completely built-up areas was classified as lower density, because the built-up density has been calculated on a larger segment having some non-built-up areas with lower density which decreased the overall built-up density value of the whole segment. In the reference polygon it was classified successfully in the relatively small segments which were homogeneously density built-up. For example, completely sealed parking lot or big compact building or encircled roads. The general problem in classifying built-up density on road network segments is that it only gives good results if the areas within the roads are homogenously built-up. In case of different types of spatial distribution of buildings within this area then the resulting built-up density indicator is not representative. In some urban environment this approach could work which are densely and regularly built-up like in some dense city centers where not much open space exists and road network is more regular and homogenously built. For the built-up area where not large spaces exist within one segment, this might not give good result.

3.3. Discussion

As we have seen from the results of the built-up density classification in Shenzhen study areas, the quantitative assessments of these outcomes, our proposed techniques (classification on ACTUAL_BUILT-UP_DENSITY level) gives better and preferred results than simply applying on the road enclosed segments (ROAD_NETWORK level), since the technique takes into consideration the heterogeneity of the built-up region inside the road enclosed portion. Anyway, this technique isn't performing admirably, for recognizing consistently separated built-up areas where structures are further separated from one another than 15 meters. Regardless of whether there is exceptionally homogeneous built-up area with normal spacing between buildings, all enclosed by road network, the methodology (with current settings of 15px grow) would make buffer around each building, yet not merging this buffer together, thus regarding each buffered area as individual section and ascertaining built-up density on this segment and not overall compact built-up zone.

One of the conceivable solutions could be expanding the pixel buffered size to accomplish merging, yet then in different areas with other built-up structure and typology, this segment area grows more into open space without any building structures and that would impact the computation of built-up density inside the section. Maybe a few rules limiting the direction of the grow develop could be executed, so the segment would grow just towards nearest built-up region, however not outside into open non-built-up space.



a) original image
b) land cover classification
c) built-up density at ROAD_NETWORK level
d) built-up density at refined ACTUAL_BUILT-UP_DENSITY level

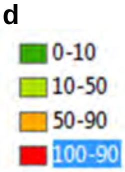


Figure 18 The three level output layer results of built-up dennsity classification (Shenzhen city study site)

Figure 18c delineates contrasts between classification of built-up density on two distinctive area units (segment at ROAD_NETWORK level and segment at ACTUAL_BUILT-UP_ DENSITY level). Figure 18c demonstrates the result of this analysis on portion enclosed by road segments (ROAD_NETWORK level) where just a single density class is recognized inside the entire fragment. Figure 22d, then again, demonstrates that if the expanded built-up segment is utilized for the density analysis, it can isolate thickly built-up area from less built-up and non-built-up regions, offering more representative understanding in the spatial dispersion of structures (or other built-up articles) and urban typology of that region.

a **b**

a) built-up density classification on the ROAD_NETWORK level
b) built-up density classification on the ACTUAL_BUILT-UP_DENSITY level

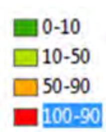


Figure 19 The three level output layer results of built-up dennsity classification (New Delhi study site)

In the figure above, illustrates the similar result for the New Delhi study site. The built-up density within road enclosed segments with homogeneously built-up area has been represented with large segment having may heterogeneous open and non-built up space on the ROAD_NETWORK level on the other hand these large heterogeneous segments are split into smaller and more homogeneous segments on ACTUAL_BUILT-UP_DENSITY level that give more representative results.

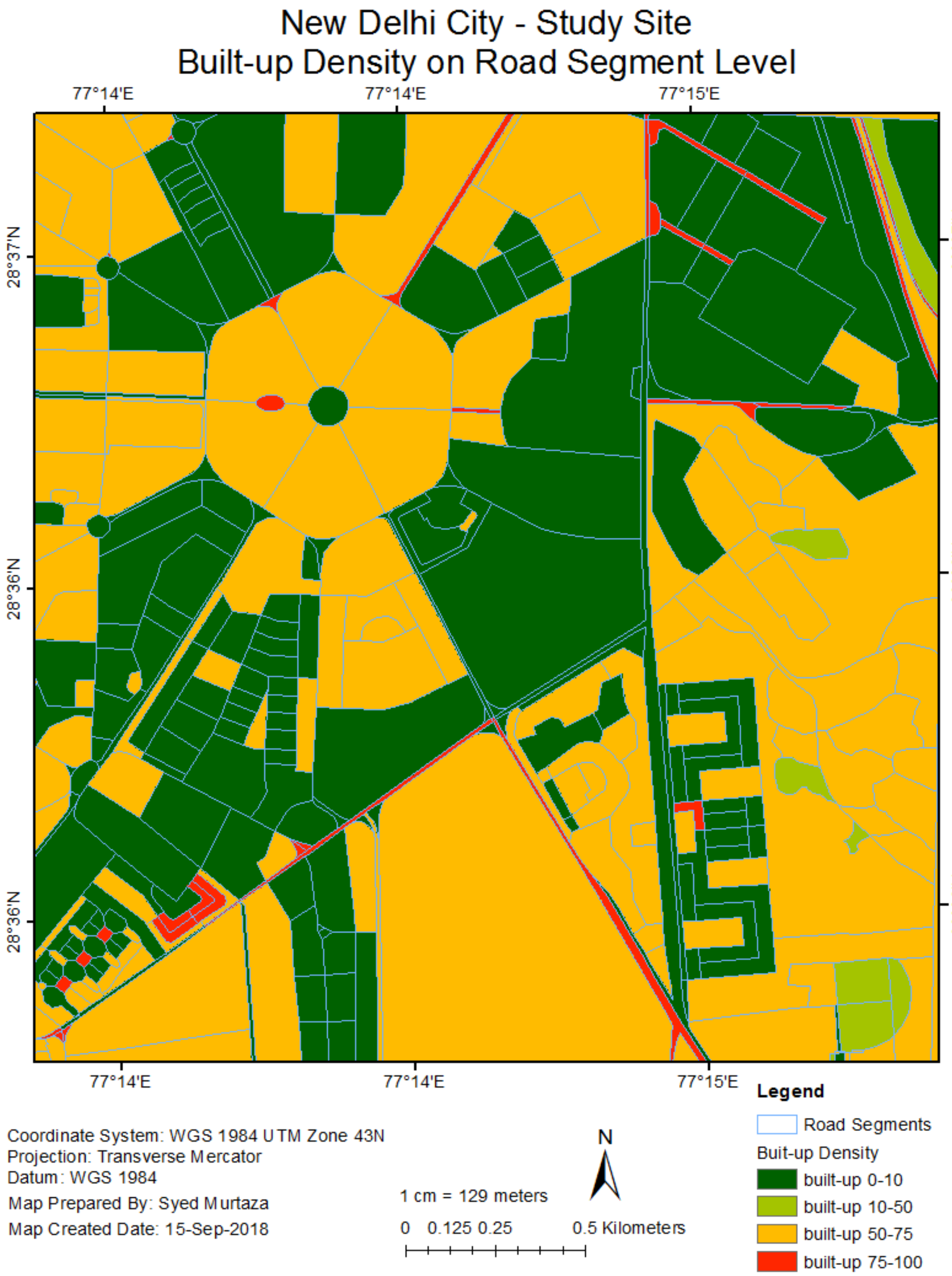
3.4. Rulesets Transferability (New Delhi Study-site)

The ruleset development procedure (eCognition ruleset) was tried on Shenzhen study site. The aim is to develop a rule-set that can be applied on another image scene with various acquisition conditions, land cover types, or building materials utilized, the atmosphere conditions, all subsequent in slightly different spectral qualities estimated for a similar land cover type in each image. The rule-sets have been applied on another scene which has diverse urban textures, urban typology and neighborhood morphology, streets structure and so on, these all have an effect on the states of the image objects (segments), made through segmentation, particularly while using layers like Sobel (highlight edges) into the Multiresolution Segmentation. So, for various images, distinctive segments are made. Nonetheless, if the scale parameter utilized is generally low (10 for our situation), individual image items may represent to individual urban structures, which is a good outcome for the segmentation which makes it a decent base for the land cover arrangement.

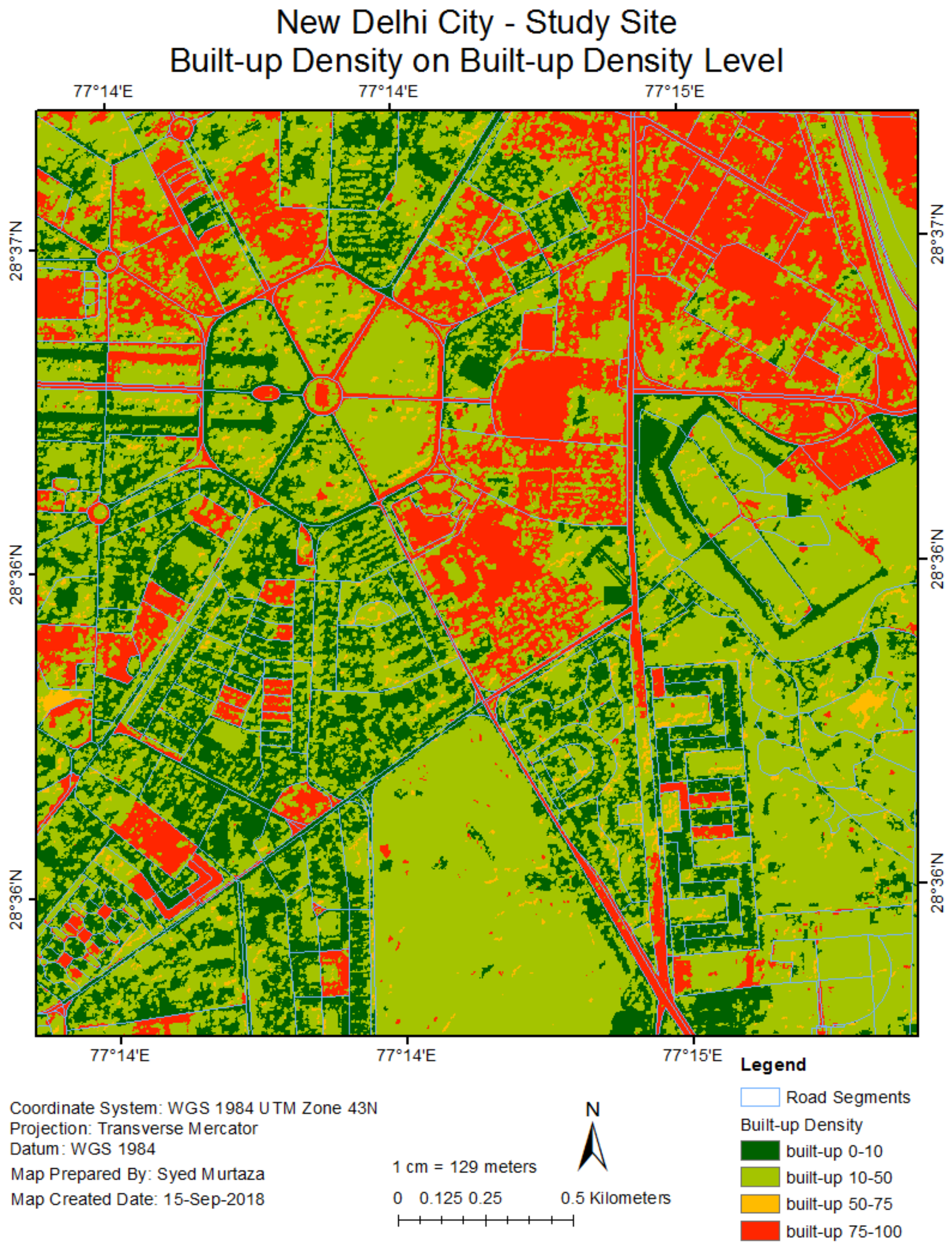
The segmentation algorithm and parameters utilized were the same for both image scenes. Nonetheless, the classification rules used to arrange some land cover classes must be optimized and improved for each image (e.g. scope of qualities, or diverse image features used), as a result of the mention spectral differences. Because of the mentioned spectral values, this image classification part of the rule set isn't transferable, generic and universally applicable, however must be upgraded for particular image conditions. Nonetheless, after effectively classifying the land cover and extricating built-up area, starting here on, all the accompanying image processing algorithm and calculations were utilized similarly, with similar parameters on the two images. As the result appears, the extended built-up zone (on ACTUAL_BUILT-UP_DENSITY level) have comparative attributes in the two images.

The best approach can recognize the two urban fabric types and classify density separately, the best result can also be obtained for openly built-up and dense areas such as buildings with trees or free space in between. Nonetheless, the issue in both images is to separate sparsely built-up areas where distance is greater than 15m, the methodology with current parameters and settings cannot identify one area segments from other in sparsely dense areas, however distinguishes just individual structures and their nearby surroundings.

The results of this methodology are anyway comparative in the two images. With this stated, we can conclude, that the methodology is transferable, with requirement for optimization of the classification rules for the land cover order for particular image. The developed procedure was tried on two distinct images. It is desirable that it is tried on more VHR images from various urban conditions to see the outcomes, look at them and affirm these conclusions. So as to increase the transferability of the developed procedure to be utilized with other VHR images and limit classification optimization efforts, input images ought to be standardized somehow, e.g. taken in the meantime of the day with comparable enlightenment conditions, or a similar season with comparative phenological conditions, or by proper atmospheric rectifications or histogram matching or image equalization methods. With a specific improvement and goals to enhance the exactness of the land cover arrangement (and in this way the related built-up classification as well), it is desired to explore more methodologies and used features to precisely separate urban zone, particularly structures. For instance, such methodology of programmed building extraction utilizing multidirectional and multiscale morphological index. Such techniques ought to be absolutely investigated and possibly incorporated in this recommended built-up density analysis techniques.



Map 5 Result of built-up density classification on ROAD_SEGMENT Level (Study site in New Delhi city)



Map 6 Result of built-up density classification on ACTUAL_BUILT-UP_DENSITY Level (Study site in New Delhi city)

Chapter-4

4. Conclusion

This master thesis was aimed to develop a semi-automatic based image classification technique to classify built-up structures in urban environment from very high resolution (VHR) imagery. As depicted in the technique, this was accomplished by separating the built-up area from the image and refining its shape by various image administrators, including pixel-based object grow (dilation), merging blending contiguous items, removing small objects and so on. This refinement was done inside the road boundaries of a street network, where similar urban structure is normal, avoiding growing of the layer over the lanes into other land used zones. OpenStreetMap road network vector layer was utilized to guarantee this. Water area was acquired via land cover classification in the previous steps were likewise used as a growing constraint with a specific order to keep the BUILT layer (broadened, generalized built-up layer) to grow into water, since there is 0 built-up density in water, and this measurement ought to be computed for urban land areas as it were.

The purpose of this shape refinement was to make shapes (region segments), which would nearly resemble shape of a general envelope of the built-up region, where the urban structure and density is fundamentally similar. The methodology was executed in eCognition software and a built-up density maps delivered for two distinctive urban scenes with various urban structuring and urban morphology. The aftereffect of built-up approach – built-up density map contrasted with reference polygons to particular built-up density classes, which were made by visual elucidation of the VHR image and accuracy assessment was performed. Confusion matrix was produced for every one of two-study area and results were examined. The built-up density was additionally computed out and about enclosed segments (ROAD_NETWORK level) and the results of this analysis were compared and the results of developed approach and discussed. Qualities and disadvantages of the methodology were distinguished and conceivable upgrades were recommended.

The outcomes demonstrate that the developed approach made various smaller segments, which were more homogeneous regarding structure of urban area and separating among structures and spacing between buildings as area units for figuring of built-up density, than any pre-defined regions, for example, land parcels, administrative regions or street enclosed segments. The methodology anyway fails in making buffered area around buildings where structures are further separated from one another than 15 meters. For this situation it makes just expanded buffered area around each building, however not a reduced segment for the entire area, so the outline and recognizable sparsely built-up region by one smaller region section was unrealistic. This issue ought to be additionally examined later on research on this theme.

4.1. Further Study and Research

We propose that this research area could be explored progressively and future research should be possible, expanding on result of this one and enhancing its outcomes, concentrating on exact outcome of compact built-up areas, even sparsely consistently built-up areas. Besides, different parameters of these outlined delineated compact built-up segments, for example, size and shape of distinguished buildings or structures, internal spectral inconstancy, edges of features, or others could be utilized to estimate the functional use of built-up area within the segment. For instance, if the buildings are extensive with brilliant rooftops and very little vegetation is near, it is expected to be a openly residential area. On the off chance that the structures are small and regularly spaced, with vegetation in the middle of, it is relied upon to be straightforwardly built-up residential area. Standards like these and others could be implemented to evaluate the land use of the segments. This would anyway require significantly more point by point and complex land cover classification scheme as a source of data for this analysis, including identification of rooftop material types, vegetation types, distinction between farming uncovered soil and exposed soil area in urban area or a building construction sites et cetera. This is extremely complex task and would presumably require extra information sources, for example, extra spectral bands, digital surface model (DSM), definite vector information of structures, or hyperspectral imagery.

4.2. Feedbacks

Despite the fact that Landsat 8 images were set up to be a part of the analysis, at last they were not utilized for the order of land cover and built-up density, in light of the fact that their spatial resolution of 15 m (pan-sharpened) was excessively coarse in correlation, making it impossible to 0.5 m spatial resolution of VHR imagery and did not turn out to be to be exceptionally valuable for this inspection, in actuality, they had rather negative impact on the outcomes. It was utilized for the most part for visual review. Built-up area index (BAEI) was computed, which indicates high qualities in the built-up area zones and was utilized to outwardly help in their identification. However, no pixel information from Landsat 8 images were utilized in any of the calculation.

The initial thesis was intended to be applied on imagery of Mazar City (Afghanistan), but due to unavailability of the high-resolution imagery, it was only performed on the free available imagery.

4.3. Technical Issues

One of the downsides of eCognition software (version 9.1.) was that client cannot determine more than two conditions to characterize the area of image object to be process, for instance characterize the standards to classify certain image objects into indicated class. This made the classification procedure more troublesome and diverse workarounds must be performed.

4.4. Improvements in the Applied Methodology

In the event that additional ancillary information sources are accessible, they could be utilized in this developed approach and could prompt better land cover classification, and subsequently to better by and large result of extended of built-up area segment and built-up density classification.

In case extra spectral bands are accessible, diverse spectral indices could be computed to enhance the land cover classification and accordingly enhance the precision of extraction of built-up area and urban structures. Hyperspectral imagery could be utilized to classify distinctive kinds of materials for recognizing streets and structures, or diverse sorts of rooftops, and so on.

On the off chance that accessible, Digital Surface Model (DSM) could be utilized to all the more precisely identify building structures and trees, since they are elevated objects and in this manner, enhance land cover classification and built-up area extraction altogether.

LiDAR point cloud information could likewise be used to identify the elevated objects and separate better among structures and streets or high-non-photosynthetic vegetation.

If available, SAR (radar) imagery of high resolution could be utilized to depict roughness of the surface and, for instance distinguish agricultural bare soil surfaces or even portray soil dampness substance and separate moist rural soil from dry urban uncovered soil (e.g. building sites).

Extra vector data of land parcels, small administrative districts or village units, city's utilitarian zones, or land use information could be integrated to enhance the formation of ideal shape of image objects of compact homogeneous built-up area for built-up density analysis.

On the off chance that accessible in precise, update vector layer of building footprints could be utilized for built-up density computation, without the need of land cover classification and building extraction from the satellite image information. This layer would represent to just structures, without streets or other man-made urban structures. In any case, this information isn't in every case unreservedly accessible and updated form, and this methodology mulls over that.

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